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Agricultural land suitability analysis: State-of-the-art and outlooks for integration of climate change analysis

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ABSTRACT

Agricultural land suitability analysis (ALSA) for crop production is one of the key tools for ensuring sustainable agriculture and for attaining the current global food security goal in line with the Sustainability Development Goals (SDGs) of United Nations. Although some review studies addressed land suitability, few of them specifically focused on land suitability analysis for agriculture. Furthermore, previous reviews have not reflected on the impact of climate change on future land suitability and how this can be addressed or integrated into ALSA methods. In the context of global environmental changes and sustainable agriculture debate, we showed from the current review that ALSA is a worldwide land use planning approach. We reported from the reviewed articles 69 frequently used factors in ALSA. These factors were further categorized in climatic conditions (16), nutrients and favorable soils (34 of soil and landscape), water availability in the root zone (8 for hydrology and irrigation) and socio-economic and technical requirements (11). Also, in getting a complete view of crop's ecosystems and factors that can explain and improve yield, inherent local socio-economic factors should be considered. We showed that this aspect has been often omitted in most of the ALSA modeling with only 38% of the total reviewed article using socio-economic factors. Also, only 30% of the studies included uncertainty and sensitivity analysis in their modeling process. We found limited inclusions of climate change in the application of the ALSA. We emphasize that incorporating current and future climate change projections in ALSA is the way forward for sustainable or optimum agriculture and food security. To this end, qualitative and quantitative approaches must be integrated into a unique ALSA system (Hybrid Land Evaluation System - HLES) to improve the land evaluation approach.

1. Introduction

Food security has become a global concern with agricultural lands facing enormous pressure from population growth (Chen, 2007; Johnston, 2003), global environmental changes including climate change (McKenzie & Williams, 2015), land degradation and rapid urbanization (Rótolo, Montico, Francis, & Ulgiati, 2015). By 2050, the global demand for agricultural food is projected to almost double (Baldos & Hertel, 2014; Godfray et al., 2010; McKenzie & Williams, 2015), raising the debate on the agricultural sustainability (Chartres & Noble, 2015; Smith, 2013). It is therefore important to prompt new agricultural systems not only to feed the growing population but also for reducing environmental impact (Mosleh et al., 2017; Rótolo et al., 2015; Smith, 2013). To address current and future food security through the efficient use of land resources, the assessment of the capability and suitability of disposable land is required through spatial based analytical and optimization approaches (Bonfante et al., 2018). For sustainable agricultural development and food production, robust and efficient management of agricultural land is required (Montgomery, Dragićević, Dujmović, & M. S., 2016). Land suitability analysis (LSA) is one of the key processes of the land use planning (Yu, Chen, & Wu, 2011) and it is a prerequisite to achieving optimum utilization of the available land resources (Kihoro, Bosco, & Murage, 2013).

LSA refers to a procedure or tool used for the identification of the most spatially appropriate pattern for locating current and future specific land uses (Collins, Steiner, & Rushman, 2001; Malczewski, 2004). LSA, therefore, is a function of specific requirements, preferences, or predictors of a defined activity (Malczewski, 2004). As such, agricultural land suitability analysis (ALSA) is a function of crop

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requirement and land characteristics reflected in final decisions (Prakash, 2003). ALSA analysis is an inter-disciplinary task requiring inputs from different streams that require different expertise including soil science, meteorology, social science, economics, management (Prakash, 2003) along with local knowledge (Rodenburg et al., 2014). Due to a large number of factors involved in decision making, ALSA can be identified as a multi-criteria evaluation (MCE) approach (Reshmidevi, Eldho, & Jana, 2009). ALSA is a spatial MCE task (Malczewski, 1999; Mendoza, 2000; Rabia & Terribile, 2013) that can be expressed in a generic model (Mendoza, 2000) as a function of factors or criteria affecting the suitability based on their respective weights. The major challenge of suitability analysis is to measure both the individual and cumulative effects of the different factors (Mendoza, 2000).

Recent technological advancements in Geographic Information System (GIS), Remote Sensing (RS), Decision Support System (DSS) and web-based application have allowed more powerful, precise and sustainable intervention in agriculture in terms of where to farm and which crop is the most suitable. DSS in agriculture is data driven computer-based systems that aims to solve unstructured problems and improve the performance of decision makers (De La Rosa, Mayol, Diaz-Pereira, Fernandez, & De La Rosa, 2004; Jones, 1993; McCown, 2002; Moore, Donnelly, & Freer, 1997). GIS serves as a tool for input, storage and retrieval, manipulation and analysis and output of spatial data while RS provides the information about the various spatial criteria/factors under consideration (Malczewski, 2004). Every ALSA method provides uncertainty due to propagated uncertainties in data sources. A wide range of methods have been developed including, but not limited to weighted averaging (Malczewski, 1999), the analytical hierarchy process (AHP) (Banai-Kashani, 1989; Cengiz & Akbulak, 2009; Saaty & Vargas, 2001), ordered weighted averaging (OWA) (Malczewski, 2006; Malczewski et al., 2003; Yager, 1988), and rule-based classification method (Reshmidevi et al., 2009; Yu, Chen, Wu, & Khan, 2011).

Some reviews on LSA were conducted before. A taxonomy of methods for generating land suitability maps has been discussed in a comparative evaluation by (Hopkins, 2007). This study revealed limitations regarding the use of ordinal, linear combination methods as well as the advantage of rules of combination of non-linear methods. Rossiter et al. (1996) discussed a theoretical framework for land evaluations from non-spatial to spatial models of single-area land suitability including land allocation problem. In their study, the authors presented the classification of land evaluation models according to several combinations of which we have: spatial and non-spatial analysis, static and dynamic concept of the resource base and land suitability, evaluation based on land qualities or not, suitability expressed by physical constraints to land use, yields, or economic value. According to the authors, a key challenge facing land evaluation is to prove its importance to face current land use problems. Although this paper suggests a unified theoretical framework to describe land evaluation, critics pointed out a lack of references to specific case studies (Bouma, 1996). Quantitative and qualitative land evaluations methods have been reviewed by (De La Rosa et al., 2004) and compared by (Manna, Basile, Bonfante, De Mascellis, & Terribile, 2009). Their analysis concluded that to estimate the suitability and vulnerability, changing land use and management practices must be based on land evaluation results. Similar conclusions were drawn from a review work on sustainable rice production in African inland valleys (Rodenburg et al., 2014). Collins et al. (2001) explored the historical development of LSA in the United States with emphasis on the artificial neural network methods as promising technologies for LSA. Malczewski (2006) developed a comprehensive survey of literature on GIS-based multi-criteria decision analysis (MCDA) also known as multi-criteria evaluation (MCE) covering many domains (e.g. environmental/ecology, transportation, hydrology/water resources, etc.). The results from their literature survey showed that almost 30% of the articles focused on land suitability problems. According to the authors, the main benefit of GIS-MCE methods is the preference of the evaluation criteria/alternatives that decision maker can incorporate in the value judgment that allows feedback for policy decision making. Although the MCE's nature of integrating several views of decision problems, critics argued the lack of a proper scientific basis (Malczewski, 2006). A good critical review of GIS-based LSA has been depicted by (Malczewski, 2004). One key element of this paper is that to correctly represent a particular land use planning problem including LSA, the right combination of both objective and subjective data and/or information is essential. Another survey of literature by (Delgado & Sendra, 2004) concerned sensitivity analysis in GIS-MCE. Sensitivity analysis, as a stage in a model evaluation, has been largely neglected and/or poorly applied in MCE (Delgado & Sendra, 2004).

According to (Fischer & Sun, 2001), ALSA tried to assess the following key research questions: *Will there be enough land for agricultural production to meet food and fiber demands of future populations? Where do shortages of agricultural land exist, and where there is room for agricultural expansion? What contribution can be expected from irrigation? Is land under forest ecosystems potentially good agricultural land? What are the main physical constraints to agricultural production? Will global warming affect agricultural potentials?* In addition, what are the socio-economic constraints to agricultural production? Likewise, land use questions are analyzed based on the knowledge level and the spatial scale considered. These two aspects of land use planning (knowledge and scale) are optimized in a K diagram by (Bouma, 1996) in which hierarchical scales (i levels or pedon levels representing the individual soil) and modeling approaches expressed in terms of five characteristics are reported, summarized in terms of knowledge levels K1–K5. In the plane of perpendicular axes (one ranging from qualitative to quantitative and the other from empirical to mechanistic), the K-levels are defined by K1 as user knowledge (empirical and qualitative), K2 as expert knowledge (qualitative), K3 as semiquantitative approach, K4 as quantitative model with general characterization of processes and K5 as detail mechanistic description of a part of the system.

Although some review studies addressed land suitability, few of them specifically focused on LSA for agriculture. Furthermore, to our knowledge, previous reviews have not reflected on the impact of climate change on future land suitability and how this can be addressed or integrated into ALSA methods. Thus, the main objective of this study is to review the current methods applied to address the previous resource questions for ALSA through a review of a wide set of case studies published in the international literature. This concerns strengths and limitations of most commonly used and new approaches, the application of GIS and remote sensing, the biophysical and socio-economic factors used in ALSA and their justifications. We further analyze the inclusion of climate change impacts in ALSA towards future planning and how uncertainties and sensitivity analyses are being included in such models.

2. Concepts and methodology

2.1. Concept of land suitability analysis in agriculture

Understanding ALSA is essential for a multitude of scientific investigations and policy applications to ensure food security and sustainable development. In this article, we classify ALSA as traditional and modern systems following (De la Rosa & C. A. V. D., 2002). Traditional ALSA methods are mainly qualitative, quantitative and parametric based mostly on a few biophysical factors that are most often edaphic. Modern systems of ALSA involve a new set of methods that deal with MCE, GIS and remote sensing with a large set of data as well as Decision Support System (DSS) (Gilliams et al., 2005; Jones et al., 1998) and web-based applications (Han, Yang, Di, & Mueller, 2012; Silva, Alçada-almeida, & Dias, 2014; Tayyebi et al., 2016) in which the ALSA procedures are implemented. Moreover, other web platforms able to make the ALSA in order to support the stakeholders at different

scales (e.g. CROPBASE https://cropbase.org/). In addition to these two systems, we further elaborate on expert systems for ALSA and agro-climatic suitability. Expert systems for ALSA use expert's opinion and knowledge to build ALSA models and they can be combined with traditional and modern approaches. In general, modern approaches to ALSA modeling often include expert's opinion but not exclusively (e.g., factors selection for rice crop suitability modeling can be based on rice farmers' experience, scientist's expertise. These parameters can also be selected based only on computer programs, for instance, random forest or the combination of the two modeling schemes). Agro-climatic suitability models are simplified form of crop models that includes mostly temperature and precipitation.

Since the elaboration of the Food and Agricultural Organization (FAO) land evaluation framework (FAO, 1976), ALSA has gained growing support among agricultural and spatial scientists. This can be explained, in part, by the recent progress in geographic information sciences, statistical modeling, and spatial analysis (Heumann, Walsh, & McDaniel, 2011). The process of ALSA is generally based on FAO-guidelines (FAO, 1976) with classification based on order, class, subclass, and unit. Land suitability Order is divided into Suitable (S) and Not Suitable (N). The class of suitability group within the order level, is aggregated into Highly Suitable (S1), Moderately Suitable (S2), and Marginally Suitable (S3), Currently not Suitable (N1), Permanently not Suitable (N2) (FAO, 1976; FAO, 2007). Suitability, in this context, can be defined in two ways. The first concerns the nature of the present or current physiography of a specific area, without improvement. The second is the potential suitability of an area for given uses through modification of one or more land attributes (such as reduction of water saturation of soil by drainage or reducing excessive slope by terracing) (Wang, Brent Hall, & Subaryono, 1990). The classification guides in strategic land use decision making when conflicting objectives are to be considered, successful and sustainable optimization of land resources for agriculture are required (Hossain, Rahman, Gopal, Sharifuzzaman, & Sultana, 2009; Nijbroek & Andelman, 2015). One aspect of the ongoing discussion on the sustainable agriculture or agricultural systems where yield is improved without harmful environmental impact and without conversion of additional non-agricultural land (Pretty & Bharucha, 2014) is the agro-ecological and socio-economical intensifications (The Montpellier Panel, 2013; Pretty & Bharucha, 2014).

The MCE methodology represents a different step-wise procedure that analyzes the relative importance of different options including land uses and land management practices by combining a set of quantitative and qualitative criteria. Even though MCE approach is essential in ALSA, the modeling scheme is not simple due to unique demand and inherent characteristics of each package in the modeling process shaped by changing environmental or socio-economic circumstances (Nguyen et al., 2015). A unified view of generally adopted methods in ALSA modeling approach could follow five steps (Liu, Jiao, Liu, & He, 2013) as depicted in Figure 1 by (Ferretti & Montibeller, 2016): (1) designing the decision process (e.g., the ALSA task) in term of types of farming or target crops; (2) structuring the MCE model by identification of the environmental requirements of crops; (3) selecting the spatial standardization functions and determination of the quantitative relationship between each considered environmental factor and the potential productivity of the considered target crop; (4) aggregation of partial performances through calculation of a suitability class or a score for a single factor for each evaluation unit; and (5) combination of the classes (e.g., maximum/ minimum rule) or scores (e.g., weighted linear combination) from all the considered factors and analysis of results and recommendations. This modelling path included human opinion meaning decisions makers, stakeholders as well as experts with different value judgements, conflicting objectives, legal requirement and intergenerational concerns on the choices made during the modelling as well as legitimation and justification of the results and recommendations that could be concerned by which crop rotation to follow, choice of crop variety or amount of chemical fertilization as well as soil management and conservation practices. The modeling path also includes the environment in terms of criteria and constraints, uncertainties, spatial alternatives and distributions that would shape the optimum and sustainable solutions.

The MCE model of ALSA is challenged by constraints of scale, data availability, validity, and mathematical translation and combination of diagnostic indicators or factors (Nguyen et al., 2015). MCE tool is usually designed to cope with a large number of attributes and various criteria modeled in a single index of evaluation (Joerin, Thériault, & Musy, 2001; Zoccali et al., 2017). The relative importance of these factors vis-à-vis the objective is expressed by weights (w_i) whereas land use under consideration is expressed as a score or suitability class (Nguyen et al., 2015). The weights are further normalized to a constant or unit ($\sum_i w_i = 1$). In MCE tasks in decision theory or multi-parameter analysis, the parameterization and combination of land characteristics for the modeling of the productive response of the target crop to a set of environmental factors represent a central and critical issue (Ahmadi Sani, Babaie Kafaky, Pukkala, & Mataji, 2016; Corona, Salvati, Barbati, & Chirici, 2008). The weights determination and combination approaches will be further discussed in this paper.

2.2. Search methodology

A relevant literature database for the review on agricultural land suitability was developed through a systematic search in online databases (using Google Scholar and Scopus). A Boolean search by keywords and phrases were used to query through scientific research engines and platforms. Initial search includes strictly suitability modeling of crops. Then we enlarged the database to land use planning research that includes ALSA analysis as well as watershed management for agricultural purposes. Keywords and expressions included *agriculture/crops and land suitability analysis*; *agricultural multi-criteria evaluations*; *climate change and agricultural suitability analysis*; *and agricultural suitability and uncertainties/sensitivity*.

All articles dealing with agricultural land suitability from site-specific, sub-regional, country level to global were included in the database. Each article was reviewed and the database was organized according to the pre-established checklist to collect meta-data (Table 1). The approach included all 'relevant' publications between the period 1990 and 2017. However, we referred to a few articles prior to the year 1990 that are important to understanding concepts or methods. We intentionally excluded the theoretical and mathematical formulations of the methods reported in the papers assessed for readability and easy understanding. In total, 166 articles were systematically reviewed and included in the database. These papers concerned solely those published between 1990 and 2017.

2.3. Literature database, papers categorization scheme, and data analysis

The classification scheme adopted in the present work concern mainly the methodology applied, the system that is modeled (whether is explicitly crop or agricultural system in general). To this end, methods are classified into four categories: (i) traditional, (ii) modern, (iii) expert-system and (iv) agro-climatic suitability methods. This classification of the methodologies is justified by the historical development of the ALSA. Each system is further categorized in a set of families (Figure 2). In this article, we refer to a family of methods as a set of approaches that are similar in their formulations and follows the same historical development. For instance, the use of random forest and maximum entropy (MAXENT) algorithm for ALSA falls under the machine learning family.

From the selected 166 papers, the key information regarding methods applied, their strengths and limitations, keys factors included in the analysis and their justifications were reported. Factors frequently included in agricultural land suitability were further aggregated in

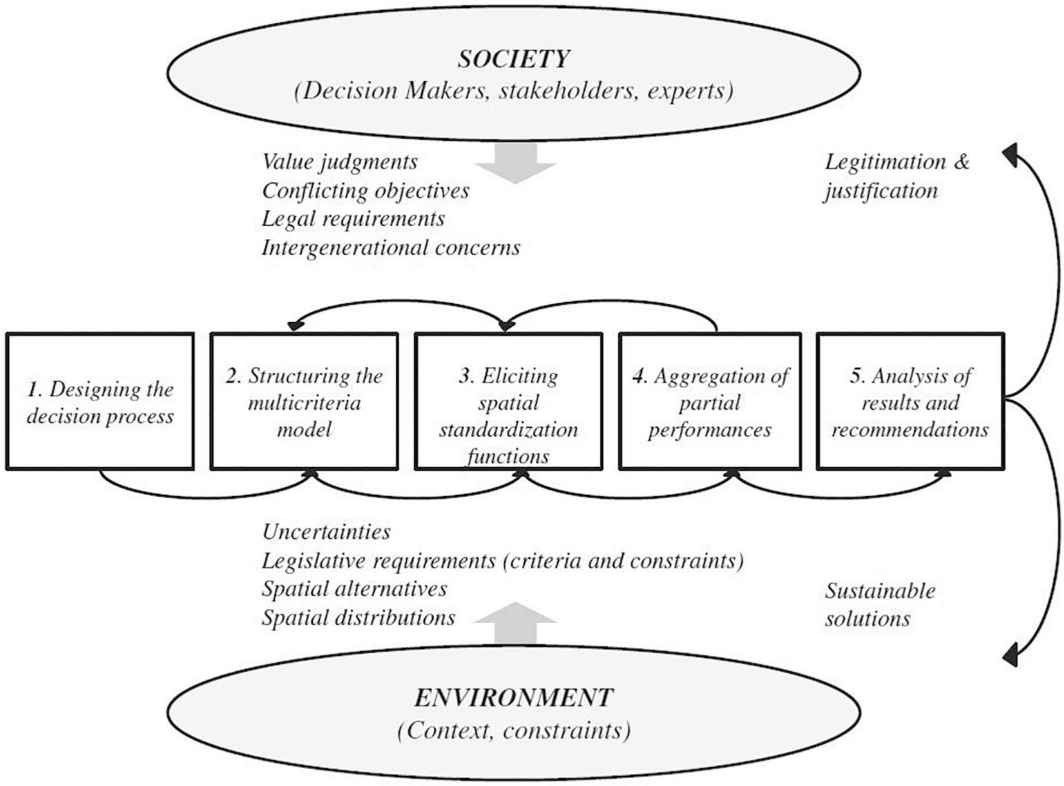

Fig. 1. Modeling steps in a socio-environmental context of MCE (Source: Ferretti & Montibeller, 2016)

biophysical factors and socio-economic constraints. Future climatic suitability for crop production was included in the review as well as uncertainties and sensitivity analysis. The above analyses were conducted through a systematic review as adopted by (Mockshell & Kamanda, 2017) who defined a systematic review as a method that collects and critically analyses multiple research studies from different sources. Furthermore, machine learning methods were used to model the most important variables that explain the inclusion or not of socio-economic analysis in one hand, and in the other hand, the uncertainty and sensitivity analysis in the articles included in the database.

3. Results and discussions

3.1. Database creation and summary

Study areas on research publications on the subject agricultural land suitability analysis (ALSA) as reviewed for the present study are mainly located in the Asia and Africa. All publications of 166 papers from more than 46 countries, regions, and sub-regions worldwide, 66 studies are from Asia, 37 from Africa, 29 from Europe, 16 from America, 11 from Australia and 7 are global studies (Figure 3). Most publications were obtained for China and Iran (both 17), followed by Australia (12), India (9), Ethiopia (7) and Italy (6). See Figure A1 in Appendix 1 for a full list of countries. This outlines that ALSA is a worldwide land use planning approach in the context of global environmental changes and sustainable agriculture debate. The literature survey revealed that, from few papers published on the subject between 1990 and 1999, the number of publications steadily increased in time as shown in Figure 4. The articles that we accessed are published in 76 journals, while publications were most frequently found in Computers and Electronics in Agriculture (13 publications), followed by Environmental Modeling and Software (10), Agriculture, Ecosystems and Environment (10) and Agricultural Systems (9). A full list of journals is provided in Figure A2 (appendix 1).

3.2. Trends in agricultural land suitability analysis

ALSA is a component of agricultural land use sustainability analysis.

Table 1
Checklist of meta-data for systematic review of agricultural land suitability analysis studies.

Item ID	Definition
Title	Title of the article or document under review
Objective	Objective of the study
Methodology	Method used to meet the study objective
Crop/Agricultural systems	Crops considered in the land suitability analysis or agricultural systems considered (e.g. irrigated or rain- red agriculture)
Keys notes/summary	Important findings from the study and limitations
Data/factors/criteria	Predictors considered in the ALSA including biophysical and socio-economic factors
Software/Computer program	Information on model implementation (e.g. use of GIS software to build the actual model) or programming (e.g. in R or python) or standalone suitability model (e.g., MaxEnt software for species suitability modeling)
Authors	Author(s)
Country/Region/Global	Country or region under study (could be single farm to global)
Journal	Journal name
Document type	Journal article, book chapter, conference paper, etc.

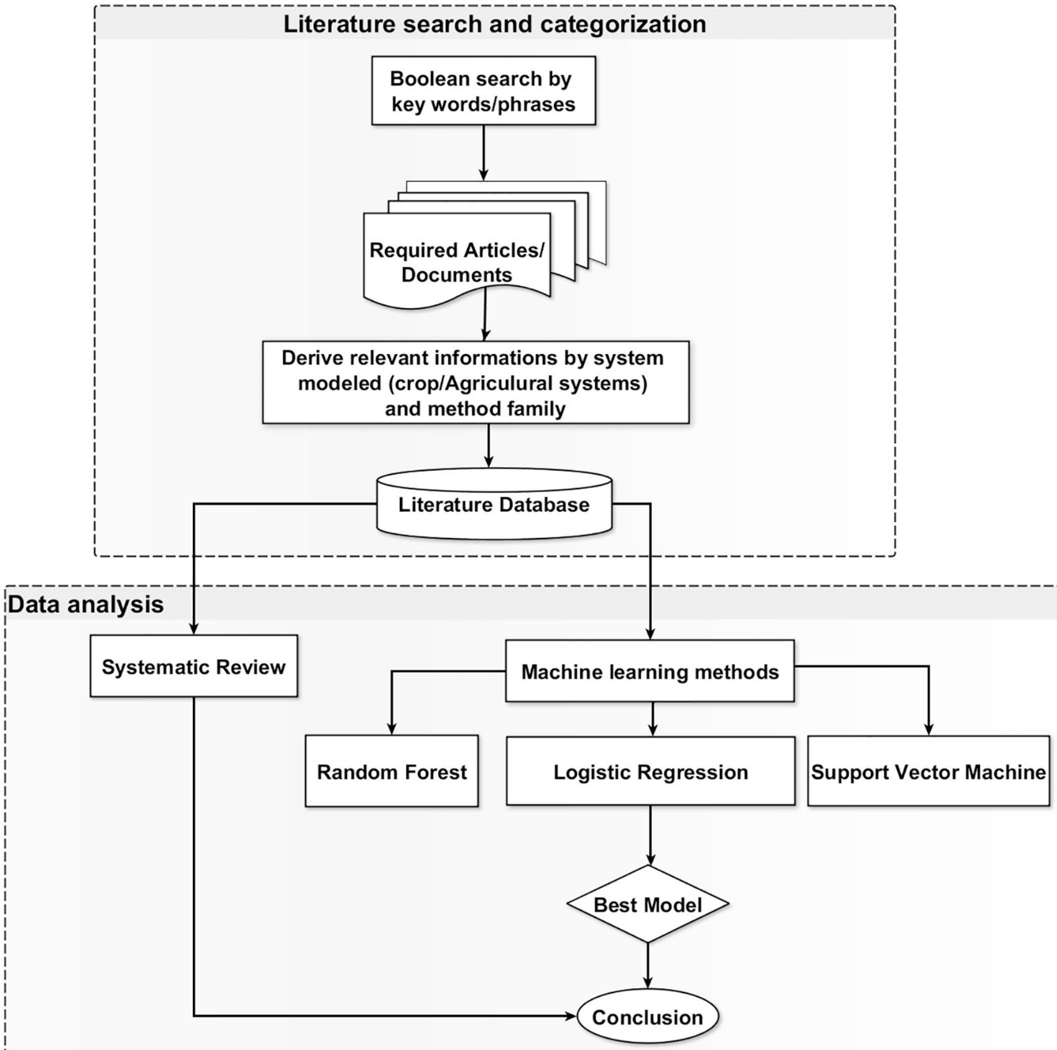

Fig. 2. Literature database building, articles' categorization and data analysis adopted in this article.

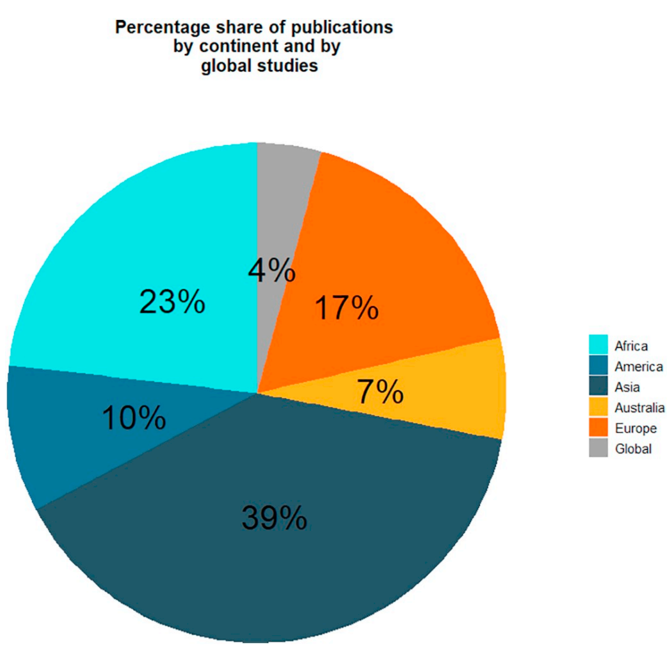

Fig. 3. Percentage share of publications per continent and global studies between 1990 and 2017

Both, the suitability and vulnerability, can define sustainability in the conceptual sense that a sustainable or optimum agricultural land use system includes maximum land suitability and minimum land vulnerability (De la Rosa & C. A. V. D., 2002). This allows environmental managers and planners to analyze the interactions between three types of factors including locations, development actions and environmental elements (Koomen, Diogo, Dekkers, & Rietveld, 2015). LSA is considered as a major component of land evaluation and the principles and method of developing land suitability maps can serve as an input in land use planning (Ritung & Agus, 2007). Methods of LSA across a wide range of domain could be classified as traditional or modern systems and are mostly based on qualitative and/or quantitative evaluations (De la Rosa & C. A. V. D., 2002).

3.2.1. *Traditional system of agricultural land suitability analysis*

In traditional systems of ALSA, crop options are based on biophysical characteristics of the land. The traditional system of ALSA follows in general trends such as qualitative and quantitative methods (De la Rosa & C. A. V. D., 2002; Chen, Messing, & Zhang, 2003; Danvi, Jütten, Giertz, & Zwart, 2016; El Baroudi, 2016). Qualitative systems are based on diagnostic factors defined in categories (highly suitable, moderately suitable, or not suitable and the system) while quantitative systems are index derived based on mathematical formulations. Qualitative evaluation can be typified in three categories: deductive, inductive and simulation modeling (Kurtener, Torbert, & Krueger, 2008). In deductive

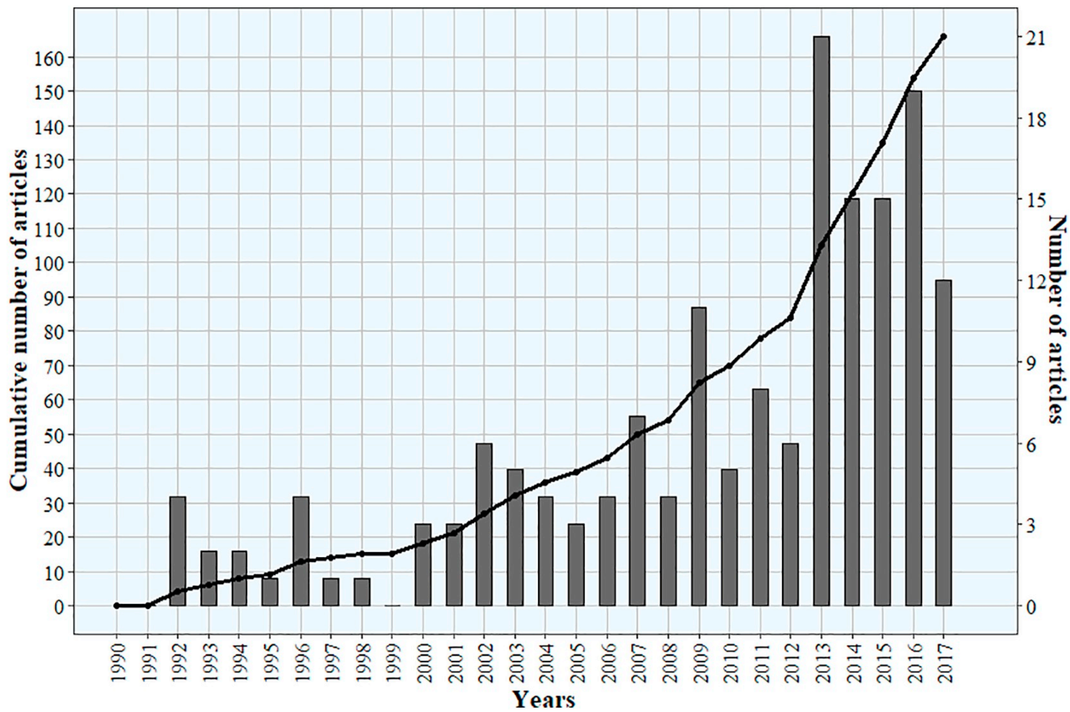

Fig. 4. Number of included articles between 1990 and 2017. The bar chart represents the number of articles reviewed per year and the line plot depicts the cumulative sum of all articles over the years.

modeling, estimated yield relative to standard yield is used as an index (Nzeyimana, Hartemink, & Geissen, 2014), while an inductive approach models land unit indices based on land characteristics (Chen et al., 2003; El Baroudi, 2016), and simulation modeling is related to non-linear systems. Some traditional systems of ALSA use several approaches such as parameters multiplying system (Albaji, Naseri, Papan, & S. Boroomand Nasab.Naseri, A. A., Papan, P., & Nasab, S. B., 2009; Motuma, Suryabhagavan, & Balakrishnan, 2016; O'Geen, 2008; Storie, 1978), parameters totalizing system, and matching system between land quality and land characteristics with crop requirements. Experience has shown that four or five factors appear to be a good average to use in multiplying systems (Storie, 1978). Additive systems allow the consideration of many more criteria, both single and in combination with the effects of other factors but failed to address the interdependence of factors**.** The difficulty in juggling factor ratings as the number of factors increases is another limitation of the additive systems. Most of the qualitative approaches assume that water requirements (in rain-fed ecosystem, this is evaluated based on the amount of rainfall from sowing to harvest while in irrigated systems, this is assessed through the volume of irrigated water) could be satisfied and optimally allocated (Sys, Ranst, & Debaveye, 1991; Sys, Ranst, Debaveye, & Beernaert, 1993; Ziadat, 2007). The methods generally follow crop requirements according to (Sys et al., 1991; Sys et al., 1993) defined in matching tables. The parametric methods like linear combination have the advantage of considering many parameters with no single one having enough weight to significantly influence the final rating (Carver, 1991; Jiang & Eastman, 2000; Romano, Sasso, Liuzzi, & Gentile, 2015). However, the approach is limited by model complexity, and problems might occur in cases where negative ratings have to be taken into consideration. Other methods such as statistical cluster analysis are designed to handle the interdependence of factors by using the statistical measures of variations on factors within clusters as measures of suitability (Cifaldi, Allan, Duh, & Brown, 2004). However, such methods failed to identify factors rating.

An example of the most traditional land evaluation system and the most widely used, the United States Department of Agriculture (USDA) land capability classification that provides conceptual definitions of capability classes regarding the degree of limitation to land use imposed by land characteristics based on permanent properties. They are also parametric methods that are derived from the numerical induced effects of various land characteristics on the potential behavior of a land-use system (Ambarwulan, Santoso, & Sabiham, 2016), but can lead to more complex rating tables. The parametric method is considered as a transitional phase between qualitative methods, which are entirely based on empirical expert judgments and standard mathematical models that would be the real quantitative systems (Bagherzadeh & Gholizadeh, 2016).

In response to the difficulties experienced with the application of the USDA's land capability system, especially in developing countries, the FAO developed a dynamic and flexible framework for land evaluation (FAO, 1976) widely adopted in ALSA. The framework is not a ready-made but a set of basic concepts, principles, and procedures for land evaluation that are considered as "valid", applicable in any part of the world and at any level, from global to single farm. The framework defines land evaluation as the process of assessment of land performance when used for specified purposes, involving the execution and interpretation of surveys and studies of landforms, soils, vegetation, climate, and other aspects of land to identify and make a comparison of promising kinds of land use in terms applicable to the objectives of the evaluation. Mendas and Delali. (2012) reported reasons for implementing the FAO classification method including simplicity, objectivity with the possibility to implement the automated procedure. The method has also been revised to incorporate GIS and remote sensing technologies (FAO, 2007). The framework describes what factors (land qualities) to consider when evaluating certain general kinds of land uses, and how to evaluate these qualities. It has been supported with a series of guidelines for land evaluation for rainfed agriculture (FAO, 1983), forestry (FAO, 1984), irrigated agriculture (FAO, 1985), and extensive grazing (FAO, 1991).

Agro-ecological innovations are important for sustainable agriculture. According to (FAO, 1996), Agro-ecological Zoning (AEZ) refers to the division of an area of land into smaller units, which have similar characteristics related to land suitability, potential production, and environmental impact. AEZ crop suitability and land productivity

assessments have been improved since digital global databases of climatic parameters, topography, soil and terrain, land cover, and population distribution are now more widely available (Fischer et al., 2002). More recently, the International Institute for Applied Systems Analysis (IIASA) and the FAO have developed Global Agro-Ecological Zones Model (GAEZ) (Fischer & Sun, 2001) and have been applied in ALSA projects (FAO, 2002; Fischer, Shah, Tubiello, & van Velhuizen, 2005; Fischer & Sun, 2001)(see Table A1 in Appendix 1). In the model, solar radiation and seasonal temperature are the main factors in the calculation of the agro-climatic potential yield while water availability, topography, and soil attributes are the main limiting factors for rainfed yields (FAO, 2002). The main elements in the framework of the models (Fischer et al., 2005) are: (1) land resources database (geo-referenced climate, soil and terrain data); (2) land utilization types (LUT) database; (2) potentially attainable crop yields estimates (3) assessments of crop suitability and land productivity; and (4) applications for agricultural development planning. However, it is important to stress that the limitation of the GAEZ approach may be due to its global scale of application. Some specific case studies of traditional systems are reported in Table A1 (Appendix 1).

3.2.2. Modern systems of agricultural land suitability analysis

Modern ALSA analysis mostly combines GIS, computer, and machines learning algorithms. According to (Malczewski, 2004), GIS-based land-use suitability analysis can be grouped into three major categories: (i) computer-assisted overlay mapping, (ii) multi-criteria evaluation (MCE) methods, and (iii) soft computing or geo-computation also known as Artificial Intelligence (AI) methods. GIS-based MCE can be considered as a process that combines and transforms a spatial data or input into a resultant decision map or output (Malczewski, 1999). The MCE procedures define a relationship between the input maps and the output maps. GIS-MCE is capable of proving a rational and objective method to make decisions in agriculture (Ceballos-Silva & Lopez-Blanco, 2003; Feizizadeh & Blaschke, 2013). The procedures involve the utilization of geographical data, the decision maker's preferences and the manipulation of the data and preferences according to specified decision rules (Akıncı, Özalp, & Turgut, 2013; Malczewski, 1999; Malczewski et al., 2003). The decision rules can be classified into multi-objective decision making (MODM) and multi-attribute decision making (MADM) methods (Malczewski, 1999). The multi-objective approaches are mathematical programming model-oriented methods, while multi-attribute decision-making methods are considered as data-oriented. Multi-attribute approaches are also referred to as the discrete methods because they assume that the number of alternatives (plans) is given explicitly (Malczewski, 2004), while in the multi-objective methods the alternatives must be generated by solving a multi-objective mathematical programming task (Chuvieco, 1993). Multi-objective methods define the set of alternatives in terms of a decision model consisting of two or more objective functions and a set of constraints imposed on the decision variables. The model implicitly defines a large decision space or a high number of alternatives in terms of decision variables. There are, however, some fundamental limitations associated with the use of these procedures in a decision-making process. The multi-objective models are often tackled by converting them to the single objective problem and then by solving the problem using the standard linear/integer programming methods (Campbell, Radke, Gless, & Wirtshafter, 1992; Chuvieco, 1993). For instance, the method has been applied in cropland allocation (Campbell et al., 1992) and the authors suggest that one major difficulty with the model concerns the level of aggregation. The model has a tendency for overestimation of efficiency relative to the existing situation.

Malczewski (2004) argues that one of the challenges related to the multi-attribute methods is the independence-among-attributes and suggest that the ideal point methods avoid some of the difficulties. The method orders a set of alternatives on the basis of their separation from an ideal point. This point represents a hypothetical decision outcome that consists of the most desirable levels of each criterion across the alternatives under consideration (Jankowski, 1995). The MODM and MADM are clearly a function of the number of alternatives under evaluation but both represent the WLC methods (Ahmadi Sani et al., 2016) that are situated at the mid-point on the continuum ranging from using Boolean "AND" operator to using Boolean "OR" operator (Chen, Zhang, & Zhu, 2011).

3.2.2.1. AHP/ANP methods in ALSA. The Analytical Hierarchy Analysis (AHP) is a MCE method proposed by (Saaty & Vargas, 2001) that decomposes a complex task into pairs of criteria (decision options) by the means of pair-wise comparison matrix, where two criteria are compared with each other at a time. It can be applied in two distinctive ways within the GIS environment: Firstly, derive the weights associated with suitability map layers that can then be combined with the attribute map layers alike the linear additive combination methods (Feizizadeh & Blaschke, 2013; Feizizadeh, Jankowski, & Blaschke, 2014; Hossain et al., 2009; Romano et al., 2015). This approach is of particular importance for a task involving a large number of alternatives represented by means of the raster data model when it is impossible to perform a pairwise comparison of the alternatives (Zolekar & Bhagat, 2015). Secondly, the AHP principle can be applied to the alternatives level (Banai, 1993) but a relatively small number of alternatives can be evaluated. Although AHP has been widely used in wide range of domains including agriculture (Table A2 in Appendix 1) and land use planning, some researchers question the theoretical functions of the method (Barzilai, 1998).

According to (Zoccali et al., 2017), AHP-MCE carries some limitations including consistency of original dataset, biased data analysis procedure, and selection of the criteria that results in uncertainties in final decisions. A web-based ALSA model, AgriSuit (Yalew, Van Griensven, Mul, & Van Der Zaag, 2016) was developed based AHP. Authors reported limitations that are inherent in the use of AHP methods meaning inconsistencies with expert judgments as well as those related to data quality. Indeed, in the AHP model, due to the fact that the pairwise comparison of factors is based on expert judgments (that are subjective), can influence the final judgement with personal preferences, uncertainties and imprecisions (Chen, Khan, & Paydar, 2010) in the weight assignment (Nefeslioglu, Sezer, Gokceoglu, & Ayas, 2013). Although the AHP techniques is an effective and superior method to determine the weights of multiple factors in systematic and logic way (Zhang, Su, Wu, & Liang, 2015), the main drawback remains the subjectivity in the expert's opinion (Mishra, Deep, & Choudhary, 2015) that may ignore interrelationships among various factors under study.

The weights assignment in ALSA via AHP can be greatly improved by following a more robust approach. According to (Zhang et al., 2015), uncertainties in the AHP model can be palliated through three options: (1) in non-scare data situation, pair-wise matrix must be derived based on scientific objective or data, (2) the relative importance of factors are estimated individually and based on more scientists' opinion. This procedure was adopted by (Zabihi et al., 2015) for land suitability procedure for sustainable citrus planning where 40 experts' opinions from citrus production and in the field of ecology–climatology were consulted using a questionnaire. (3) More attention should be paid to the upper limit. The upper limit is a consistency ratio (CR) that must be less than 0.1 for a pair-wise matrix judgment to be accepted (Saaty & Vargas, 2001) and largely adopted in ALSA (Table 2). To minimize the interrelationship among various factors included in the AHP approach, data reduction method such as principal component analysis (PCA) can be used to linearly combine factors as few new variables. This approach has been applied by (Ceballos-Silva & Lopez-Blanco, 2003) to delineate the suitable areas for the maize and potato crops. Another alternative is to combine other methods with the use of the AHP technics. For instance, (Deng et al., 2014) combines fuzzy method and AHP techniques to calculate the suitability of land for alfalfa cultivation while (Li et al.,

Table 2
Number of criteria and reported consistency ratio (CR = < 0.1).

Crop	Number of criteria	Consistency ratio	Reference
Rice	6	0.08	Kihoro et al. (2013)
Dry-farm land	7	0.05	Feizizadeh and Blaschke (2013)
Irrigation suitability	8	0.04	Feizizadeh and Blaschke (2013)
Agricultural system	9	0.07	Akıncı et al. (2013)
Potato	9	0.03	Ceballos-Silva and Lopez-Blanco (2003)
Agricultural system	10	0.05	Yalew et al. (2016)
Agricultural system	11	0.03	Romano et al. (2015)
Saffron	21	0.03	Maleki et al. (2017)

2012) combined AHP and the grey relational analysis (GRA) method to evaluate the suitability of the tea crop. Many tasks with uncertainties like ALSA in MCE systems can be solved through the optimization of grey relational coefficients in grey systems (Li et al., 2012).

Another variant of the AHP technique is the Analytical Network Process (ANP). Zabihi et al. (2015) reported three categorizations of the ANP application including modelling decision problems for the selection of the best alternative with conflicting and interrelated criteria; an existing framework can be analyzed by the prioritization of the interrelated elements within the framework (Asan & Soyer, 2009) and finally, indirect influences of various elements and their relative significance on one another within the framework. Alike AHP, the ANP method is used to build the relative weights of the evaluation criteria but uses the network with inner and outer dependences without the need to specify the location in the levels (Zabihi et al., 2015). This allows the representation of the identified relationships between intangible assets and strategic goals.

3.2.2.2. OWA method in ALSA. The Ordered Weighted Averaging (OWA) is another MCE method used to improve AHP application in agriculture. Jiang and Eastman (2000) argue that the OWA approach provides an extension to and generalization of the conventional map combination methods in GIS. OWA is a class of multi-criteria operators developed by (Yager, 1988) and involves two sets of weights: criterion importance weights and order weights (Malczewski et al., 2003). The AHP is usually applied to determine the criterion importance weights. The method has been applied to evaluate the potential of a rural coastal area restoration of manor farms (Romano et al., 2015) while (Malczewski et al., 2003) used the method as a watershed management option. Jiang and Eastman (2000) suggest that OWA should be tested in a variety of decision-making situations to determine how it may help decision makers in the real world considering that as a relatively new topic of research. The OWA has been combined with AHP and Fuzzy in a framework of MCE of irrigated pasture (Chen et al., 2011).

3.2.2.3. LSP and ELECTRE Tri methods in ALSA. Another MCE method is the GIS-based Logic Scoring of Preference (LSP) method (Montgomery et al., 2016). The method is based on the observed properties of human reasoning. According to (Montgomery et al., 2016), the main advantage of the LSP is the nonlinear aggregation of criteria based on soft computing models of simultaneity and substitutability. In addition, the LSP method is capable to include a large number of inputs while maintaining the importance of each input throughout the MCE. More than 30 criteria have been used as input to the LSP model for the evaluation of land capability and suitability for agriculture (Montgomery et al., 2016). This high number of inputs is not always the case of the AHP where the average number of criteria reported in most of the ALSA case studies is around 10 (Table 3). A MCE of sequential decision approach including a filtering and section process was adopted as an alternative to pairwise comparison or rating methods in agricultural landscape planning that acts as a sieving function to eliminate the need to further consider alternatives that are unfit according to earlier criteria (Saroinsong, Harashina, Arifin, Gandasasmita, & Sakamoto, 2007). Other studies adopted the ELECTRE Tri method to study the agricultural suitability of wheat crop (Mendas and Delali, 2012). This method solves the sorting problem and uses discrimination thresholds based on fuzzy logic principles. The method has the merit of the aggregation mode of decision-maker performances and the assignment of the potential alternatives to predefined categories (Mendas and Delali, 2012).

3.2.2.4. Fuzzy methods in ALSA. ALSA is usually considered as a fuzzy modeling task (Burrough, MacMillan, & Deursen, 1992; Ranst, Tang et al., 1996) as the problem is associated with high degree of uncertainty (Zoccali et al., 2017). Conventional methods such as maximum limitation, Storie index and Sys parametric approach are based on experience-dependent decisions. Furthermore, the Boolean conventional method treats both spatial units and attribute value ranges as exactly specifiable quantities that ignore the continuous nature of soil and landscape variation and uncertainties (Burrough et al., 1992; Van Ranst et al., 1996). Also, (Jiang & Eastman, 2000) arose concerns about aggregation methods and data standardization during WLC approach. According to (Bagherzadeh & Gholizadeh, 2016), the fuzzy method differs from the conventional land evaluation procedures by the use of an explicit weight for the effect of each land quality on crop performance and the way of combining the evaluation of land qualities into a final land suitability class or land suitability index. The fuzzy method is considered a robust approach that can be used to fill the gap between, Boolean and WLC methods (Jiang & Eastman, 2000) and parametric methods.

The ALSA based-fuzzy method consists of the determination of the quantitative impact of land qualities on LSA by minimizing a value outside a specified range (Bagherzadeh & Gholizadeh, 2016). Three main processes are used during the modeling phase: (1) fuzzification, fuzzy rule inference, and defuzzification. Fuzzification is the process by which the quantitative values of the environmental parameters are converted into linguistic variables of order suitable or not suitable by the means of membership functions. During this process, all the crispy factor values are mapped to a common scale (i.e., values of 0 to 1) (Feng et al., 2017a). The determination of membership value of the environmental factors is done with fuzzy rule inference (e.g., use of empirical IF-THEN rules) while defuzzification converts the membership values into suitability index (Feng et al., 2017b). The application of fuzzy logic in land suitability modeling has the advantage of a user-defined tolerance to the class limits in the form of the transition zone (Burrough et al., 1992) or partial membership giving due consideration to the uncertainty involved (Deng, 1999).

Although the fuzzy logic approach to land-use suitability modeling is shown to have fewer limitations than conventional techniques, the approach is subjected to some drawbacks. The main limitation associated with the fuzzy logic approach to land use suitability analysis is the lack of a definite method for determining the membership function (Tang, Van Ranstb, & R. G., 1997). The membership functions and weights play keys role in the fuzzy-based modeling of ALSA but are mostly based on expert's knowledge; considered a major constraint

Table 3
Selected ALSA under climate change. For details on scenarios (A1, A2, B1, B2, A1B, A1FI, A1B, A2 B1), referred to the Special Report on Emission Scenarios by (IPCC, 2000). The RCP 8.5 is one of the Representative Concentration Pathways (RCPs). The RCPs are used for making projections based on anthropogenic GHG emissions driven by population size, economic activity, lifestyle, energy use, land use patterns, technology and climate policy. The RCPs include a mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0) and one scenario with very high GHG emissions (RCP8.5). See IPCC Fifth Assessment Report (AR5) (IPCC, 2014) for full definitions of the RCPs.

Crops/agricultural systems	Objectives	Scenarios	Climatic parameters	Global Circulation Models (GCMs)	Suitability model	References
Viticultural zoning	To understand how suitability for viticulture is changing under climate change	Reference climate: 1971-2005; future climate (2010-2040, 2040-2070, 2070-2100); scenarios: RCP 4.5 and RCP 8.5	Daily minimum and maximum temperature, and precipitation	CMCC-CM, ECHAM5	Hybrid Land Evaluation system (HLES)	Bonfante et al. (2018)
Maize	Effects of climate change on land suitability for maize	Emission scenario 1A ENSEMBLE	Daily minimum and maximum temperature, and precipitation	Coupled atmosphere-ocean global climate models (AOGCMs)	Hybrid Land Evaluation system (HLES)	Bonfante et al. (2015)
Wheat, maize, rice, and soybean	Heat stress on crops	Baseline climate: 1971–2000; Future climate: 2071 to 2100 using the A1B emissions scenario	Daily maximum and minimum temperature	Global 1.125° gridded GCM at the National Institute for Environmental Studies (NIES)	FAO/IIASA Global Agro-Ecological Zones model (GAEZ)	Teixeira et al. (2013)
Cassava, maize, wheat, sorghum, rice, and millet	Future hotspots of hunger in Sub-Saharan Africa	Historical: CRU TS2.1 (1990-1999); future climate: 2030-2039 Four scenarios are used: A1FI, A2, B1, and B2.	Temperature, solar radiation, precipitation	-	GEPIC	Liu et al. (2008)
Sweet potato, sorghum, maize, soybean, wheat	Impacts of climate change on land suitability for rain-fed crop diversification	Historical: 1995-2014; Future climate: RCP 8.5 up to 2100	Precipitation, Evapotranspiration, temperature		MicroLEIS DSS through the application of Almagra and Terraza models	Liambila and Kibret (2016)
Cereal production (including wheat, maize and other coarse grains)	Impacts of climate change on agro-ecosystems	Scenarios: A1FI, A1B, A2, B2, B1 for the period 1990-2080	temperature, precipitation, solar radiation, vapor pressure deficit	HADCM3, ECHAM, CSIRO, CGCM2, NCAR-PCM	FAO/IIASA agro-ecological zone model	Günther Fischer et al. (2005)
43 crops	Impact of climate change on selected crops suitable	A2a	Temperature, precipitation	WorldClim data as a baseline, downscaled HADCM3 and CCCMA models.	Ecocrop is implemented in DIVA-GIS	Lane and Jarvis (2007)
Sorghum	Evaluate the likely impacts of climate change on agricultural production	Baseline (1961–1990) from WorldClim; SRES-A1B of 24 different GCMs for the future period 2020–2049 of CMIP3	Temperature, precipitation	24 statistically downscaled Global Circulation Models (GCMs)	Ecocrop model	Ramirez-villegas et al. (2013)
Barley, Cassava, Groundnut, Maize, Millet, Oil palm, Potato, Rapeseed, Paddy rice, Rye, Sorghum, Soy, Sugarcane, Sunflower, wheat	Modelling global crop-suitability	SRES A1B by ECHAM 5 (compare 2071–2100 with 1981–2010)	Temperature, precipitation	ECHAM 5	Fuzzy Logic approach	Zabel et al. (2014)
Banana and Coffee	suitability and spatial delineation of coffee and banana production zones	19 Coupled Model CIMP5 RCP scenarios 2.6, 4.5, 6 and 8.5. Historical: 1985–2005; future period up to up to 2050	Temperature, precipitation,	19 GCMS	Global Environmental Stratification (GEnS), consensus mapping with BiodiversityR package and Fuzzy overlay	Ranjitkar et al. (2016)
Paddy irrigation	Predicting the impacts of climate change on paddy irrigation	A1, A2, B1, B2 Baseline: 1961–1990	Precipitation, reference evapotranspiration	HadCM3 model	Spreadsheet model based CROPWAT methodology	De Silva et al. (2007)
Arabica coffee	Impact of climate change on suitability to grow Arabica coffee	The 2050s on the 21 GCMs used in the IPCC AR4 for scenario A2a of the IPCC's SRES	Temperature, precipitation	21 GCMs	MaxEnt algorithm	Ovalle-Rivera et al. (2015)

(Ranst et al., 1996; Liu et al., 2013) and few have investigated or calibrated the weights based on data or samples (Liu et al., 2013). According to (Davidson, Theocharopoulos, & Bloksma, 1996), weights of environmental factors should be based on data and knowledge of the relative importance of differentiating land characteristics to crop growth. This approach has been adopted by (Liu et al., 2013) in the evaluation of agricultural land by integrating a genetic algorithm (GA) with a multi-criteria evaluation based fuzzy inference system, a self-adapting system that calibrates its evaluation criteria by self-learning from land samples. In their proposed GA-optimized fuzzy inference model, the criteria for land evaluation are encoded into chromosomes, i.e., each chromosome represents a solution for the evaluation criteria system (Liu et al., 2013). Other memberships functions have been proposed for ALSA including Euclidean distance (Wang et al., 1990), bell-shaped curves or S-functions (Ranst et al., 1996), parabolic, sigmoid, linear functions (Zhang et al., 2015), Gaussian combination membership function (Bagherzadeh, Ghadiri, Darban, & Gholizadeh, 2016) etc. Different functions have been tested in fuzzy overlay by (Lewis, Fitts, Kelly, & Dale, 2014) in fuzzy logic-based spatial suitability model for drought-tolerant switchgrass. Their results showed that "GAMMA" function best integrates the low and high memberships of multiple suitability criteria. The bell-shaped membership functions are all S-functions, which may be used to represent increasing notions (e.g., nutrient availability, effective rooting depth) while their complements are used to represent decreasing notions (e.g., slope) (Tang et al., 1997). Simplifications of the bell-shaped functions may result in other membership functions such as the triangular and trapezoidal membership.

The fuzzy method has been extensively adopted in ALSA (see Table A3 in Appendix 1). In recent years, Fuzzy AHP is mostly adopted for sensitivity and uncertainty analysis of LSA in agriculture (Zhang et al., 2015, de la Rosa, 2002). However, some critics have pointed out the fact that one should never use fuzzy arithmetic on AHP judgment matrices (Saaty, 2006) while pairwise comparisons obtained from a decision maker are crisp (Krejčí & Pavlačka, 2016). Nevertheless, in a situation where the decision making is subjected to imprecision and vagueness or the pairwise comparisons are vague, fuzzy AHP is to be applied (Krejčí & Pavlačka, 2016).

3.2.2.5. Machine learning methods in ALSA. In recent years, large environmental datasets have been made available for environmental modeling through remote sensing, climate models, direct field data collections, etc. Such big data processing for ALSA are not always trivial when it comes to automating the process. With the advancement of the power of computers, machine learning algorithms have emerged as key modeling tools in ecology and agriculture. Broadly defined, machine learning is a data analysis method that automates the process of analytical modeling of input data by using statistical analysis to predict an output value with an acceptable range. The approach is also known as artificial intelligence (AI). The use of MCE through AI methods are considered as the future of the LSA. AI is the modern computational techniques that can help in modeling and describe complex systems in the context of decision making.

Artificial Neural Networks (ANNs) are among the most advanced methods in ALSA analysis, a non-linear mapping structures, which by means of their architecture attempt to simulate the biological structure of the human brain and nervous system (Mas, Puig, Palacio, & Sosa-López, 2004). The method consists of processing elements (nodes) or artificial neurons, organized in a parallel and interconnected structure; and the problem to be solved guides the choice of the type of networks to be used. Lek and Guegan (1999) reported two commonly used ANNs including (1) multi-layer feed-forward neural networks trained by backpropagation network (BPN) that constructs a model based on examples of data with known outputs (BPN is based on the supervised learning); (2) and self-organizing mapping known as Kohonen Network, in which the relevant multivariate algorithms seek clusters in the data. Wang (1994) provides an example of ALSA for wetland rice, soybean, sugarcane, pasture, and acacia crops in the north coast of West Java, Indonesia or paddy field evaluation (Jiao & Liu, 2007). According to these studies, ANN is an effective tool for pattern analysis and the method should be used in pattern classification where decision rules are of greater complexity. The method has the advantage of having good capability in dealing with nonlinear multivariate systems to learn from data relationships that are not otherwise known and, to generalize to unseen situations (Carvalho et al., 2013; Elizondo, Hoogenboom, & R. W. M., 1994; Wang, 1994). Therefore, ANNs make powerful tools for models, especially when the underlying data relationships are unknown (Mas et al., 2004). ANNs can be used to achieve greater accuracy by formulating ALSA into pattern classification problem (Wang, 1994). This advantage is confirmed by (Bagherzadeh et al., 2016) who applied parametric-based NNs and fuzzy methods to model land suitability of soybean production. Their results showed that the values of regression coefficient between the estimated land index values by both models with the observed soybean yield in each land unit varied between 0.610 and 0.514 for neural networks and fuzzy approaches, respectively. Similar results of land suitability evaluation of Alfalfa production using parametric-based NNs and TOPSIS modeling were observed with values of correlation coefficient varying between 0.926 and 0.880 respectively.

Although ANNs provide strong advantages in pattern classification, the application of the model in ALSA is not without limitations. One the major challenge in ANNs is the definition of the network structure, i.e. the number of layers and of nodes in the layers. According to (Wang, 1994), a design criterion is to use as few as possible layers and nodes because large numbers of layers or nodes lead to higher computing costs and a very long training time. A large number of input layers may also result in over-fitting or noise modeling. To avoid this drawback, (Lek et al., 1996) suggested two elements that need to be taken into account: the number of neurons in the structure and the stopping point or a number of iterations in the training. From their case study, results stabilized around 8 hidden nodes after 1,000 iterations. The cross-verification is also used as a means to avoid noise modeling. In cross-verification, a part of the dataset is actually not used for training but to keep an independent check on the progress of training (Mas et al., 2004). This ability, however, may become a disadvantage because the model could be over-specific to the training data which reduces the generalization capacities of the ANN (Mas et al., 2004). For instance, (Mas et al., 2004) modeled deforestation of two different periods using ANNs. While the ANNs modeled successfully deforestation in the first period (used as the training set), they were not able to predict deforestation of the following period because very specific to particular patterns of deforestation of the training period. The models lost the general trends of deforestation processes and therefore were not able to predict correctly deforestation for the following period. The loss of generalization capacity may be solved by reducing the number of input variables by applying input reduction statistics like PCA. The black box nature of the ANN model is said to be the major limitations of the method. The ANNs failed to establish the functional form of the relationship between the input variables and the output (Lek & Guegan, 1999; Mas et al., 2004). However, ANNs may be useful in identifying the most important variables and the functional form of the relationship between them and the output(s) (Mas et al., 2004). Examples of the applications of the ANNs are reported in Table A4 in Appendix 1.

Another application of machine learning algorithm in ecology and agriculture is the likelihood or suitability of occurrence of land use such as agricultural crop types based on the presence data only. This approach has great potential for use, particularly, where extensive land use information is often difficult to obtain (Heumann, Walsh, Verdery, McDaniel, & Rindfuss, 2013). One of this method is the Maximum Entropy (MaxEnt) model. MaxEnt output is the spatial distribution of probabilities that the environment factor in a given pixel is suitable for the species in question (Gumma, Thenkabail, Fujii, & Namara, 2009).

The MaxEnt model is a niche-based model that assumes the distribution of observations, i.e., presence data represents the realized niche (Heumann et al., 2011). The model has been applied in ALSA (Gumma et al., 2009; Heumann et al., 2011) but has some limitations. Although incomplete dataset is often used in the MaxEnt modeling, the model is sensitive to sample size and distribution; and the model assessment is not straightforward (Heumann et al., 2011).

3.2.2.6. Expert system and expert opinion in ALSA. A full discussion on the use of expert's opinion in agriculture is beyond the scope of the present work. Our point here is to highlight the strengths and weakness of expert's opinion and existing expert systems for ALSA. A comprehensive review of the role of expert opinion in environmental modeling has been discussed by (Krueger, Page, Hubacek, Smith, & Hiscock, 2012). According to this paper, an expert can be anyone with relevant and extensive or in-depth experience in relation to a topic of interest. With regards to environmental modeling, experts can be categorized as scientific experts (e.g., agronomist, climatologist, etc.), professional experts (e.g., rice farmers), and non-professional experts (e.g., representatives of stakeholder groups). In ALSA, expert opinion is frequently used through parameter selection and weighting importance. The most common method of ALSA that involve expert opinion is the AHP and its variants techniques (see Table A2 in Appendix 1). The number of experts involved varies from few to workshop group (Bojórquez-Tapia, Diaz-Mondragón, & Ezcurra, 2001; Zabihi et al., 2015), from literature review (Bydekerke, Van Ranst, Vanmechelen, & Groenemans, 1998) to direct consultation (Brandt, Kvaki, Butterbach-Bahl, & Rufino, 2017) or modeling of farmers' knowledge (Steiner, 1998; Zurayk et al., 2001; Messing and Fagerström, 2001; Cools, De Pauw, & Deckers, 2003; Sicat, Carranza, & Nidumolu, 2005). An expert system or knowledge-based system in agriculture is a computer program or framework that simulate the problem-solving capacity of an expert from individual disciplines in agriculture (Prasad & Babu, 2006). An example of expert system is the Automated Land Evaluation System (ALES) with several applications in agriculture (Ambarwulan et al., 2016; D'haeze, Deckers, Raes, Phong, & Loi, 2005; Wandahwa & Van Ranst, 2014; Yizengaw & Verheye, 1995). The system is based on the FAO framework and can include socio-economic aspects. The Mediterranean Land Evaluation Information System (Micro-LEIS), a Decision Support System (DSS) is another integrated system for land data transfer and agro-ecological land evaluation with GIS capabilities (de la Rosa, Anaya-Romero, Diaz-Pereira, Heredia, & Shahbazi, 2009). Other systems include Intelligent System for Land Evaluation (ISLE)(Tsoumakas & Vlahavas, 1999), Land Evaluation using an Intelligent Geographical Information System (LEIGIS)(Kalogirou, 2002), web-based GIS online consulting system (Jayasinghe & Machida, 2008) and Agriculture Land Suitability Evaluator (ALSE) (Elsheikh et al., 2013). The strength and limitations of these systems are discussed by (Elsheikh et al., 2013). The expert systems applications in ALSA are reported in Table A5 in Appendix 1. The use of expert systems is a faster and more flexible solution in addressing classification problems compared with procedural sequential algorithms and the classifications are based on given knowledge rather than by making assumptions or by using heuristic algorithms (Kalogirou, 2002). The main drawback of knowledge-based systems is the subjectivity in the decisions (Yizengaw & Verheye, 1995). Although stakeholder involvement in participatory planning and consensus building can be difficult, the role of experts in ALSA is important because they act as technical advisors (Bojorquez-Tapia, Diaz-Mondragon, & Ezcurra, 2001; Brandt et al., 2017). In such complex modeling, a plurality of expertise is required.

3.3. Agricultural Land suitability analysis under climate change perspectives

According to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5), the negative impact of climate change on crop yields across a wide range of regions have been more common than positive impacts (IPCC, 2014). Climate change will induce major impacts on water availability and supply by modifying rainfall, evaporation, runoff, and soil moisture storage (Olesen & Bindi, 2002) as well as important variation in temperature regime. According to (Lobell, Schlenker, & Costa-Roberts, 2011), evidence from recent past temperature increase in cropping regions and growing seasons of most countries showed a significant decline in global wheat and maize production. Also, the stress on crops and livestock will become global in character due to climate change induced extreme growing season temperature variation (Battisti and Naylor, 2009) with the negative response of global yields of wheat, maize, and barley to increased temperature (Lobell & Field, 2007). A Study on dry season irrigated rice showed that, while maximum temperature effects were insignificant on rice yield, increase in each 1°C in growing-season minimum temperature in the dry season resulted in grain yield declined by 10% (Peng et al., 2004). According to authors of this article, their report provides a direct evidence of decreased rice yields from increased nighttime temperature associated with global warming (Peng et al., 2004). It is therefore clear that climate change will result in changes in agricultural income, inducing shifts in the production areas of food and non-food crops and reduced crop productivity (IPCC, 2007; IPCC, 2014).

Although climate and weather influence crop production components (both cropping area and production), most studies focused on their influence on crop yield (Iizumi & Ramankutty, 2015). It is therefore argued that one should consider cropping area to a larger view of the future climate change impact on food production (Iizumi & Ramankutty, 2015). Identification of suitable agro-ecological zones and understanding climate change-related issues on land suitability for crop production are important for improved production and livelihoods of smallholder farmers (Liambila & Kibret, 2016; Ranjitkar et al., 2016). Climate change is expected to impact agriculture as a function of location (Lane & Jarvis, 2007) with resulting effects depending on current climatic and soil conditions, the direction of change and the availability of resources and infrastructure to cope with change (Olesen & Bindi, 2002). Suitable areas for crop cultivations of some important crops including rice will shift as results of climate change (Lane & Jarvis, 2007).

ALSA considering climate change has been recognized as important (Lane & Jarvis, 2007; Liambila & Kibret, 2016; Romeijn, Faggian, Diogo, & Sposito, 2016). Study on socio-economic and climate change impact on agriculture showed that very suitable and suitable land in Sub-Saharan Africa will decrease under certain scenarios (Fischer et al., 2005). Temperate and sub-tropical agricultural areas might bear substantial crop yield losses due to extreme temperature episodes and therefore a need to develop adaptation strategies and agricultural policies able to mitigate heat stress impacts on global food supply (Teixeira, Fischer, Van Velthuizen, Walter, & Ewert, 2013; Günther Fischer et al., 2005). Crop relocation and improved land management are identified as key for adaptation and mitigation to climate change (IPCC, 2007) and hence called for LSA for crops.

ALSA can also be assessed using agro-climatic indicators known as agro-climatic suitability. They are a simplified form of crop modeling and are usually made spatial explicit. Two parameters are usually included in the suitability modeling: temperature and precipitation from which many other indicators can be derived to assess the agro-climatic suitability of a given crop. In addition to these two variables, the yield of the crop is usually used for the model evaluation. An example of agro-climatic suitability is the land suitability of grain maize, winter wheat and cauliflower in Europe using water requirement satisfaction index (Kenny, Harrison, Olesen, & Parry, 1993). Two challenges are reported with the development and application of such model at coarser scales to run more sophisticated model including (1) the lack of climate and soils data of sufficient spatial and temporal resolution and (2) the lack of crop phenological and yield data that can be used for model validation.

Another example of agro-climatic suitability is the EcoCrop model

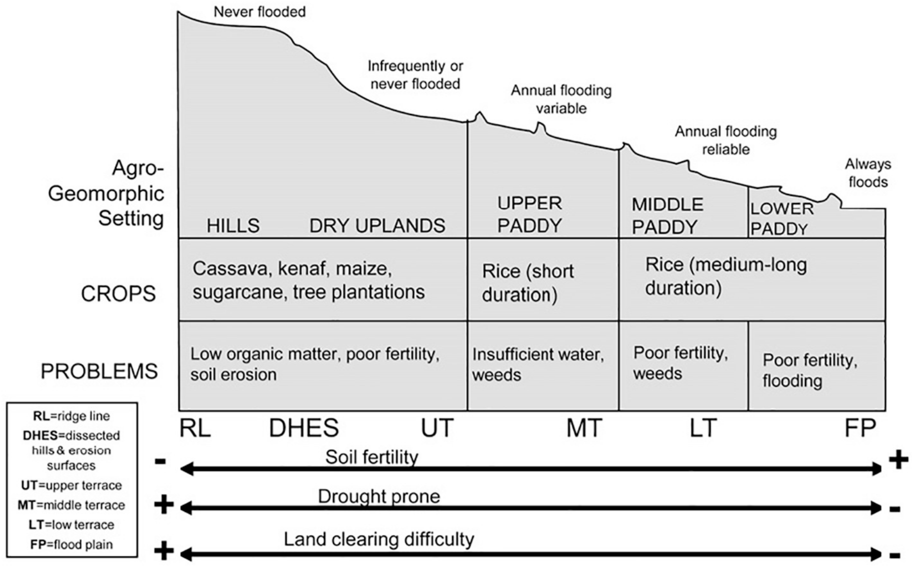

Fig. 5. Idealized cropping systems: gradients and constraints (Source: Heumann et al., 2011).

(Lane & Jarvis, 2007; Ramirez-villegas, Jarvis, & Läderach, 2013). The EcoCrop model as described in (Ramirez-villegas et al., 2013), is based on a set of indicators derived from variables temperature and rainfall such as the absolute range, defined by Tmin-C and Tmax-C (minimum and maximum absolute temperatures at which the crop can grow, respectively) for temperature, and by Rmin-C and Rmax-C (minimum and maximum absolute rainfall at which the crop grows, respectively) for precipitation; and second, the optimum range, defined by Topmin-C and Topmax-C (minimum optimum and maximum optimum temperatures, respectively); and Ropmin-C and Ropmax-C (minimum optimum and maximum optimum rainfall, respectively); and Tkill to illustrate the effect of a month's minimum temperature. The total suitability score is the product of the temperature and precipitation suitability surfaces calculated separately (Ramirez-villegas et al., 2013). Authors reported limitations inherent to their model. Although the EcoCrop model tries to simulate the non-linear effects of climatic indicators, the model failed to simulate the interaction during the phenological phase that may lead to overestimation of climatic suitability. Suitability indices derived from this model are therefore hardly interpretable. In the model, annual and growing season rainfall and temperature are equal, making difficult the calibration of the modeling process.

Fixed duration of the growing season may facilitate the selection of parameters (Ramirez-villegas et al., 2013), but poses a constraint as physiologically crops do not have always the same growing season. To avoid these constraints, an agro-climatic suitability model has been proposed by (Mkhabela, Bullock, Gervais, Finlay, & Sapirstein, 2010; Holzkämper, Calanca, & Fuhrer, 2011; Gouache et al., 2012; Holzkämper, Calanca, & Fuhrer, 2013). These models dynamically determine phenophase-specific climate sensitivities. A crop phenological development is a function of growing degree days (GDDs), which sum thresholds defining the transition from one phenological stage to the next (Holzkämper et al., 2011). This approach has advantages of providing more accurate information about the effects of climate on particular plant processes occurring during specific crop development phases, and the agro-climatic analysis can be applied to the entire crop cycle (Caubel et al., 2015). During the modeling process, normalization of climatic indicators links indicators to suitability indices and normalization functions are passed on expert's opinion. This is the main drawback of the method because depending on the expert assessment, and especially depending on the expert's area of knowledge, aggregation functions may vary (Caubel et al., 2015).

Specific dynamic crop models have been used in ALSA. For instance, the Decision support system for agrotechnology transfer (DSSAT) model (Jones, 1993; Jones et al., 1998) has been applied to estimate the suitability and productivity of dryland maize (Estes et al., 2013). Also, the EPIC model has been made spatially explicit, so-called GEPIC to assess future hotspot of food insecurity in sub-Saharan Africa (Liu et al., 2008) while a spreadsheet model based on CROPWAT methodology was used to access variation of the impacts of climate change on paddy irrigation (De Silva, Weatherhead, Knox, & Rodriguez-Diaz, 2007). These crop models imply details analysis of a crop life cycle that might be important for final yield, are more agronomic in nature (Zabihi et al., 2015). However, setting up such models can be time and data consuming and especially if management variability has to be considered (Caubel et al., 2015). Specific case studies of crop models and agro-climatic modeling in ALSA are reported in Table A6 in Appendix 1.

In ALSA under climate change, the choice of both modeling approach and its driving parameters are important. The modeling approaches in this context can be based on the methods discussed in the previous sections. This implies that results from ALSA under climate change are inherent to limitations related to such models. For instance, (Estes et al., 2013) adopted multi-models approach by comparing mechanistic and empirical model projections of crop suitability and productivity of dry-land maize. From their analysis, empirical models (MAXENT and GAM – Generalized Additive Model) outperform the mechanistic model (DSSAT) in terms of predicting productivity and produce comparable results for suitability. However, under climate change analysis, authors suggested that mechanistic models may be the modeling choice because changing climate is likely to produce novel climatic conditions beyond the range upon which empirical models are trained.

To improve the limitations related to the crop models and standard land evaluation approaches in ALSA under climate change, a new method, known as Hybrid Land Evaluation System (HLES) was developed by (Bonfante, Al, De Lorenzi, Manna, & Basile, 2015). The HLES combines qualitative (standard land evaluation) and quantitative (simulation model) approaches considering plant demands, estimated future temperatures, and soil water regimes. The approach consists of three fundamental steps including evaluation of thermal conditions of the plant (step 1), the qualitative approach (step 2) and the quantitative approach (step 3). The qualitative approach allows consideration of some less dynamic soil features that influence crop cultivation, providing the possibility to identify environmental limits and possible management solutions. Thus, step 2 as a traditional empirical land

Table 4
Choice and justification of climatic indicators.

Factors	Justification	References
Potential/Actual Evapotranspiration (P/AET)	Climate factors such as rainfall and potential evapotranspiration are among the crucial factors that affect the suitability of an area for irrigation.	Worqlul et al. (2017)
Chill hours	Chill hours represent an indicator to ensure cold enough conditions to optimize nut production.	Kidd et al. (2015)
Arity index (AI)	AI links precipitation and evapotranspiration to define climatic zones	Ranjitkar et al. (2016)
Diurnal temp	Suitable diurnal temperature fluctuations to ensure seed self-regeneration and therefore long-term persistence of the crop.	Abson et al. (2012); Mbũgwa et al. (2015)
Growing degree days (GDD)	To represent growing season length and the cumulative heat requirements for plant growth.	Ramankutty et al. (2002); Feng et al. (2017)
Length of growing period (LGP)	LGP represents the number of days when soil moisture and temperature permit crop growth.	Batty (1994); Gumma et al. (2009); Fischer et al. (2002); Masoud et al. (2013)
Length of the phenological period (LPP)	To account for effects of phenological development on biomass accumulation and crop yields.	Holzkämper et al. (2013)
Relative Humidity	Some crops must be planted in areas where RH is low (e.g., Saffron). RH is important during the months of flower pollination. High RH results in poor pollination, which in turn leads to a low number of formed fruits (e.g., cherimoya).	Bydekerke et al. (1998); Maleki et al. (2017)
Solar radiation	Solar radiation has an important effect on crop growth and yield. Solar radiation is essential for photosynthesis but excessive amounts of solar radiation can cause photo-damage to plants.	Holzkämper et al. (2013); Hoffmann et al. (2014); Rhebergen et al. (2016)
Sunshine hours	Sunshine hours are used as an estimate of solar radiation.	Zabihi et al. (2015); Rhebergen et al. (2016)
Temperature	Precipitation and temperature are the two major variables that could greatly impact growth and final yield of biofuel crops, and rain-fed cropping system.	Feng et al. (2017)
Temperature degree day (TDD)	TDD is a measure of heat accumulation, very useful in crop planting and management.	Wilson & Barnett (1983); Ranjitkar et al. (2016)
Winds	Agricultural productivity is highly affected by meteorological parameters including wind speed.	Hatfield et al. (2011); Zabihi et al. (2015)

evaluation procedure, identifies limiting features that are not covered by crop simulation models (e.g. flooding, surface stones, salt) (Bonfante et al., 2015). The quantitative approach based on physically based simulation models in step 3 emphasized the importance of simulation modeling approach as the only way to have a quantitative evaluation of climate change impacts on the crop. However, they underline the importance of a land evaluation approach to cover all aspect of the environment that are not treated by simulation modeling application. The direction is that qualitative and quantitative approaches must be integrated into a unique ALSA system (Hybrid Land Evaluation System - HLES) to improve the land evaluation approach. The approach is recently done with a dynamic viticultural zoning that confirmed the potential of the hybrid land evaluation approach to studying crop adaptation and crop responses to climate change, as well as the importance of simulation modeling application (Bonfante et al., 2018).

In addition, ALSA under climate change impact assessment studies are mostly based on Global Circulation Models (GCMs) (see Table 3). GCMs represent one powerful tool to generate the characteristics of

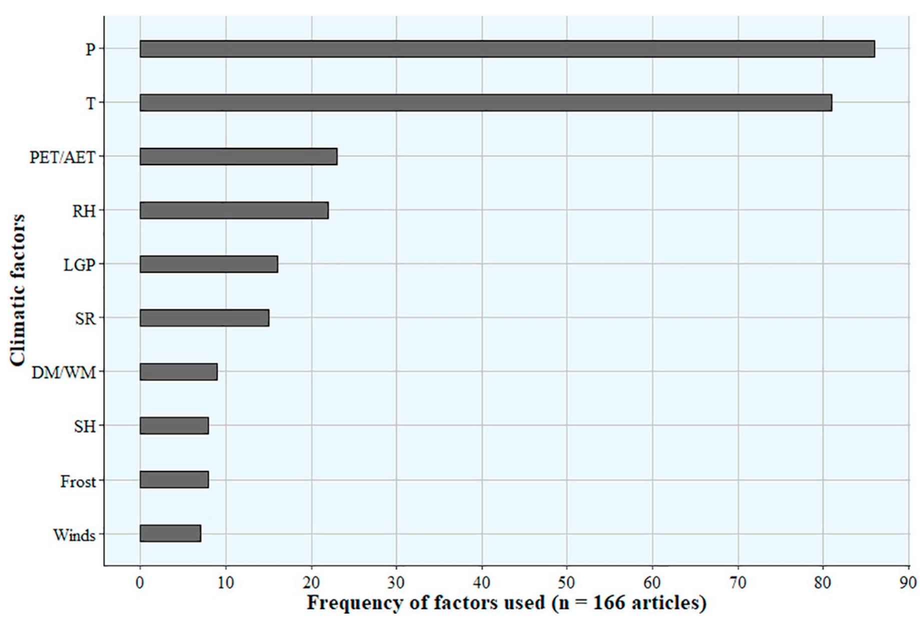

Fig. 6. The frequency of the top 10 climatic factors used in ALSA. P, precipitation; T, temperature; PET/AET, potential/actual evapotranspiration; RH, relative humidity; LGP, length of the growing period; SR, solar radiation; DM/WM, length of dry/wet months; SH, sunshine hours; Frost, frost hazard; Winds, winds speed.

Table 5
Choice and justification of hydrology/irrigation indicators

Factors	Justification	References
Discharge	Surface water discharge can be an important factor in agricultural watershed management.	Peterjohn et al. (1984); Gumma et al. (2009); Masoud et al. (2013)
Depth to water-table (DWT)	DWT is used as one of the indicators in the irrigated cropping system.	Chen et al. (2007); Chen et al. (2010); Chen et al. (2013)
City well heads	This factor was considered as one of the most important in developing watershed management strategies.	Malczewski et al. (2003)
Ground Water	Groundwater can be a viable option for supplementing surface water resources for irrigation. It has a slow response to climate variability and requires less treatment than surface water.	Liu et al. (2008); Siebert et al. (2010); Worqlul et al. (2017)
Irrigation water use	Very import in the irrigation system and water management.	Dubovyk et al. (2016)
Stream order	Stream orders are often considered in inland valleys suitability analysis (e.g., 4th order steams and 5th order streams are considered highly suitable for rice crop).	Gumma et al. (2009); Masoud et al. (2013)
Wetness	Soil wetness or wetness index can be linked to soil drainage, an important topographic factor for ALSA. Soil wetness constraints mean that effective risk management is crucial to ensure farm productivity and to avoid long-term damage to the soil resource.	Brown (2017); Munene et al. (2017)

future climates under anthropogenic forcing, i.e. under present and projected future emissions of greenhouse gases. Yet, it is well known that GCM projections present significant uncertainties, due in part to issues of scale resolution, leading to incomplete models (Fischer et al., 2005). Modeling uncertainty results from an incomplete understanding of the climate system or an inappropriate representation of the complex climate system within a single model (Daccache, Keay, Jones, Weatherhead, & Stalham, 2011). For this reason, many studies use the outputs of multiple future climate projections to increase the confidence in the climate projections (Fischer et al., 2005; Lane & Jarvis, 2007; Ovalle-Rivera, Läderach, Bunn, Obersteiner, & Schroth, 2015; Ranjitkar et al., 2016). In addition, the models disagree on the direction of changes in rainfall in SSA and this adds to the uncertainty associated with the use of climate projections in ALSA. In contrast to multiple GCMs consideration, other ALSA considered only one GCM (De Silva et al., 2007; Liu et al., 2008; Teixeira et al., 2013; Zabel, Putzenlechner, & Mauser, 2014) due to data availability, confidence in the model performance and resolution. As an example, (Teixeira et al., 2013) used Global 1.125° gridded Circulation Model (GCM) at the National Institute for Environmental Studies (NIES) model because of the high temporal resolution of climate data provided (i.e. daily fields of maximum and minimum temperature) which is required to assess the impact of extreme events vis a vis the objective of their study.

3.4. Factors frequently used in agricultural land suitability analysis and their justifications

Indicators are the driving factors in ecosystems sustainability assessment and ALSA modeling. According to (Kurtener et al., 2008), indicators are a subset of the many possible attributes that could be used to quantify the condition of a particular landscape or ecosystem. These indicators, considered valuable tools to understand complex environmental system evaluation and decision making, can be derived from biophysical, economic, social, management and institutional factors (Walker, 2002). They are measurable attributes of the environment that can be monitored through field observation, field sampling, remote sensing or compilation of existing data. Some key elements are important to consider when selection factors (Kurtener et al., 2008) for ecosystem modeling and ALSA including reliability, interpretability, data availability, established threshold values need to set class boundaries (e.g. crop maximum limitation tables), and known links to processes (e.g. precipitation can be selected as an important factor in rain-

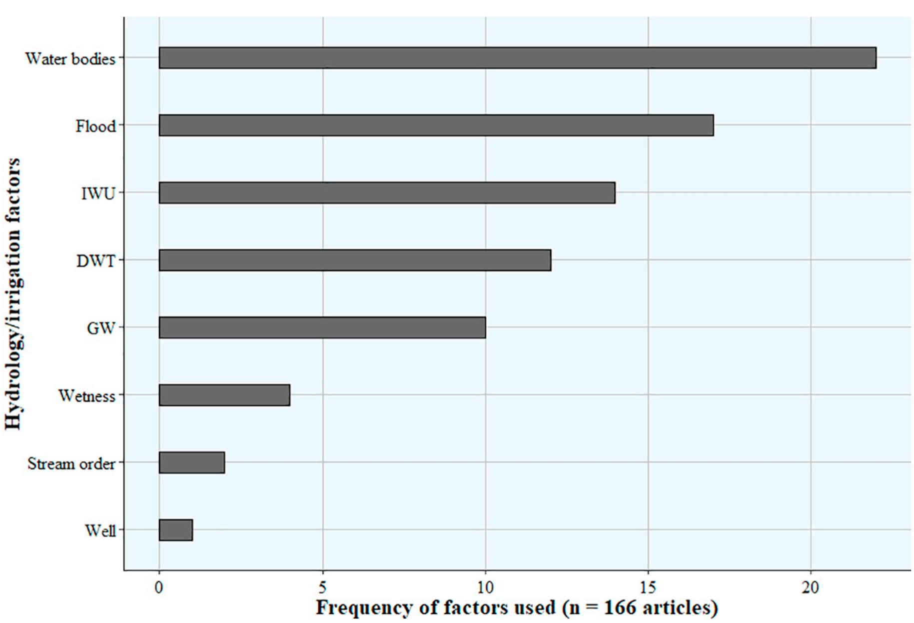

Fig. 7. The frequency of the top 10 hydrology/irrigation factors used in ALSA. Water bodies, for open water, rivers and discharge; Flood, flooding hazards; IWU, irrigation, irrigation water use; DWT, depth to water table; GW, groundwater; Wetness, soil wetness index; Stream order; Well. Frequently used climate factors in ALSA as reported in the papers reviewed for the present article are reported in Table 8.

Table 6
Soil and landscape attributes

Factors	Justification	References
Aspect	Aspect influences the degree of sunlight exposure, and thus southern and western aspects are usually assumed to be most capable for agriculture	Akıncı et al. (2013)
Base saturation percentage	High values base saturation limit crop growth.	Avellan et al. (2012); Ambarwulan et al. (2016); Danvi et al. (2016)
Boron toxicity	Boron toxicity can limit plant growth in soils of arid and semi-arid environments	Nable et al. (1997); Chen and Paydar (2012)
Bulk density	Bulk density is an indicator of the compactness of the soil. Bulk density is considered to be a measure of soil quality due to its relationships with other properties (e.g., porosity, soil moisture, hydraulic conductivity, etc.).	Liu et al. (2008); Yi and Wang (2013)
Clay	Clay is important in moisture retention for crop growth.	Braimoh et al. (2004)
Cation exchange capacity	CEC provides a buffer against soil acidification and can influence the soil's capacity to hold onto essential nutrients. It is frequently included in ALSA.	Ambarwulan et al. (2016); Kalogirou (2002); Ahamad et al. (2000)
Fertility (Nitrogen-N, Phosphorus-P, and Potassium-K)	Soil fertility is the most important characteristics of the soil and it has a great impact on crop productivity. N-P-K are the primary nutrients but vary with time-based on specific crop cultivation.	Dadhich et al. (2017)
Effective depth	Effective rooting depth is related to soil depth. The shallow soil may restrict development of plant root due to which the plant may suffer adverse conditions in the limited soil volume.	Akıncı et al. (2013); Schiefer et al. (2016); Dadhich et al. (2017); Feng et al. (2017)
Elevation	Variation in elevation has an impact on soils, microclimatic effects, and other processes that could affect land suitability.	Yi and Wang (2013)
Erosion hazard	Erosion is an indicator of soil degradation with substantial loss of soil nutrient.	Ambarwulan et al. (2016); Bagherzadeh and Gholizadeh (2016)
Land Use Land cover-LULC	Knowledge of existing land use provides information about the land availability. Land use data helps to identify the productivity of an area for a given cropping system.	Liu et al. (2008); Yi and Wang (2013); Worqlul et al. (2017)
Gypsum	Highly gypsic soils (> 10% gypsum) should be avoided as, under irrigation, they may subside as the gypsum is dissolved from the soil, under irrigation.	Toma et al. (1999); Avellan et al. (2012); Abdelfattah (2013); Al-Yamani et al. (2013); Abdelrahman et al. (2016)
Hard pan	Hard pan or bedrock depth refers to soil depth to a physical restriction that significantly reduces the movement of water and air through the soil.	Abdelfattah (2013); Al-Yamani et al. (2013); Baroudy (2016)
Hydraulic conductivity	Hydraulic conductivity is an important soil physical property for determining infiltration rate, irrigation, drainage practices, and other hydrological processes. It controls water and solute transport, its assessment at the field scale is important in evaluating agronomic performances.	Baroudy (2016); Chen et al. (2010); Chen et al. (2013); Carof, De Tourdonnet et al. (2007)
Organic Carbon/Matter	Ideal source of plant nutrients in soils, important in maintaining soil structure, soil tilth and reducing soil erosion. Soil OC indicates the organic matter content in the soil which often creates the basis for the successful use of mineral fertilizers. The combination of organic matter and mineral fertilizers provides the suitable environmental conditions for the crop as the organic matter improves soil properties and mineral fertilizer supply the plant is Needed.	Rounsevell et al. (1999); Braimoh et al. (2004); Bandyopadhyay et al. (2009); Schiefer et al. (2016)
Rockiness/Stoniness	Estimate proportion of surface rock and stone	Chen and Paydar (2012); D'Angelo et al. (2000); Akıncı et al. (2013)
Salinity (Electrical conductivity)	Soil salinity indicates the total concentration of soluble salts in the soil. In root zone, the presence of soil with a substantial amount of natural salt lead to a reduction of soil water which is extracted by plant and may cause a nutrient imbalance that could affect plant growth and limit crop yields by causing the low osmotic potential of the soil solution.	Esmaeelnejad (2016); Feng et al. (2017)
Sand	Cultivation of sandy soil often leads to soil degradation.	Braimoh et al. (2004)
Silt	Silt and clay increase surface area of the soil and amount of plant available water decreases the leaching potential.	Schiefer et al. (2016)
Slope	The slope is a crucial factor affecting vegetation structure and soil erosion. The slope is the important aspect of the surface as well as for internal soil water drainage as both characteristics play a major role in the growth of the crop.	Yi and Wang (2013); Esmaeelnejad (2016)
pH	An important factor in soil productivity and plant growth. It provides the information about the solubility and thus potential availability or phytotoxicity of elements for crops and subsequently specifies the soil suitability for a specific crop. Nutrient availability is also a function of pH.	Halder (2013); Braimoh et al. (2004); Esmaeelnejad (2016)
Texture	The texture is one of the important parameters of soil. Most of the physical properties of the soil depend upon textural class. The soil textural class most capable for agriculture are loam, which contains a mix of sand, silt, and clay particles. Soil textural class influences a soil's ability to drain water, be aerated and hold onto moisture.	Halder (2013); Esmaeelnejad (2016)
Alkalinity/Sodicity (Exchangeable Sodium Percentage-ESP)	Sodicity affects the productivity of crop by reducing the water availability and soil permeability to plant root.	Pessarakli (2016); Behzad et al. (2009); Esmaeelnejad (2016); Abdelrahman et al. (2016)
Soil depth	Soil depth determines roots growth as well as the presence of a volume of water and air in the soil.	Bandyopadhyay et al. (2009)
Soil Drainage	Play a key role in air and soil water regime. Well-drained soil results in deeper rooting of crops. Also, gives an indication of the soil moisture conditions.	Braimoh et al. (2004); Munene et al. (2017)
Water holding capacity	Water holding capacity estimates total available water in the root zone and determines the need for irrigation.	Benke and Pelizaro (2010); Ismail et al. (2012); Chen and Paydar (2012); Zolekar and Bhagat (2015)

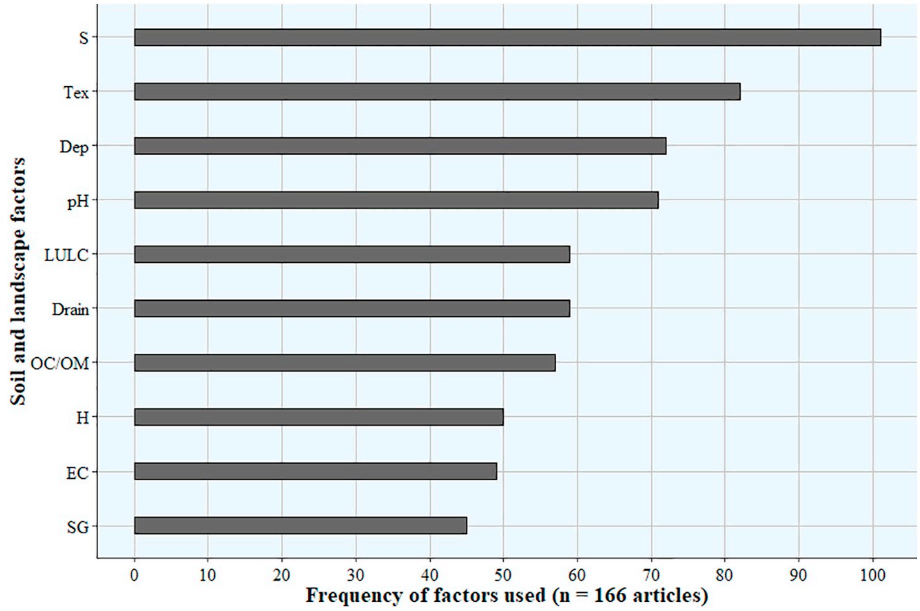

Fig. 8. The frequency of the top 10 soil and landscape factors used in ALSA. S, Slope; Tex, soil texture; Dep, soil effective depth; pH, soil pH; LULC, land use land cover; Drain, soil drainage; OC/OM, organic carbon, organic matter; H, elevation; EC, electrical conductivity or salinity; SG, soil type, soil group.

fed agricultural system). Also, considering known links to factors, environmental and socio-economic factors heavily influence the vulnerability of the agricultural sector adaptation to climate change (Abson, Dougill, & Stringer, 2012; Brandt et al., 2017). The factors used in ALSA have been variously linked to biophysical factors; socio-economic; and technical constraints. For instance, considering biophysical characteristics, agricultural land suitability is explicitly linked to topography (see Figure 5). In such ecosystems, hills, (uplands, high, medium, low) terraces and floodplains represent different suitability levels for a given crop (e.g. rice).

In the present work, several factors were reported from the reviewed articles and grouped under 69 factors (see supplementary materials for a full list of factors). These factors were further categorized in climatic conditions (16 factors), nutrients and favorable soils (34

Table 7
Social-economic and technical indicators.

Factors	Justification	References
Female participation in economic activities/Gender	Female participation in economic activities is understood as an indicator of women empowerment and economic development. Gender inequality increases the susceptibility to sudden changes and threats as such as climate change. Integrated conservation agriculture and agroforestry have the potential to promote gender equality and improve livelihoods for women and men while supporting mitigation and adaptation.	Beuchelt and Badstue (2013); Brandt et al. (2017)
Literacy rate/Education	The literacy rate is an education indicator. High literacy reflects enhanced the adaptive capacity of making informed decisions regarding viable coping strategies under climate change.	Eliasson et al. (2010); Alkimim et al. (2015); Brandt et al. (2017)
Population/Population density	Access to market is important to agricultural activities. It is sometimes used as a proxy for market access and ability to transport inputs.	Alkimim et al. (2015); Nijbroek and Andelman (2015); Worqlul et al. (2017)
People employed for agricultural activities/Labor force	Considered as people that possess some level of knowledge of agricultural activities	Deng et al. (2014); Alkimim et al. (2015)
Average income	Expected income per hectare of given crops can influence the choice of which crop to be grown by farmers.	Kalogirou (2002)
Distance to road/accessibility	Land use is often also influenced by ease of access to networks for the transport of supplies or produce. This factor is usually most important in remote areas.	Mendas and Delali (2012); Elaalem (2013); Worqlul et al. (2017)
Credit systems	Define the easy access of farmers to credit.	Masoud et al. (2013)
Distance to source of water	Could be important in a system whereby small-scale farmers have to travel to fetch water for irrigation.	Cengiz and Akbulak (2009)
Markets Availability	Market access plays a key role in agricultural development in many ways. For instance, a study showed that the relatively limited use of chemical fertilizers in Sub-Saharan Africa has indeed been variously linked to market access constraints.	Erenstein (2006); Elaalem (2013)
Extension system/ Technical assistance	Extension systems transfer knowledge from researchers to farmers, advising farmers in their decision making, educating farmers to be able to make similar decisions in the future, enabling farmers to clarify their own goals and possibilities and stimulating desirable agricultural development.	Gebremedhin et al. (2006)
Land tenure	Land tenure is a social concern. Considered as important in case of ALSA for large-scale investment, land tenure not always systematically include in the modeling process due to lack of data.	Masoud et al. (2013); Nijbroek and Andelman (2015)

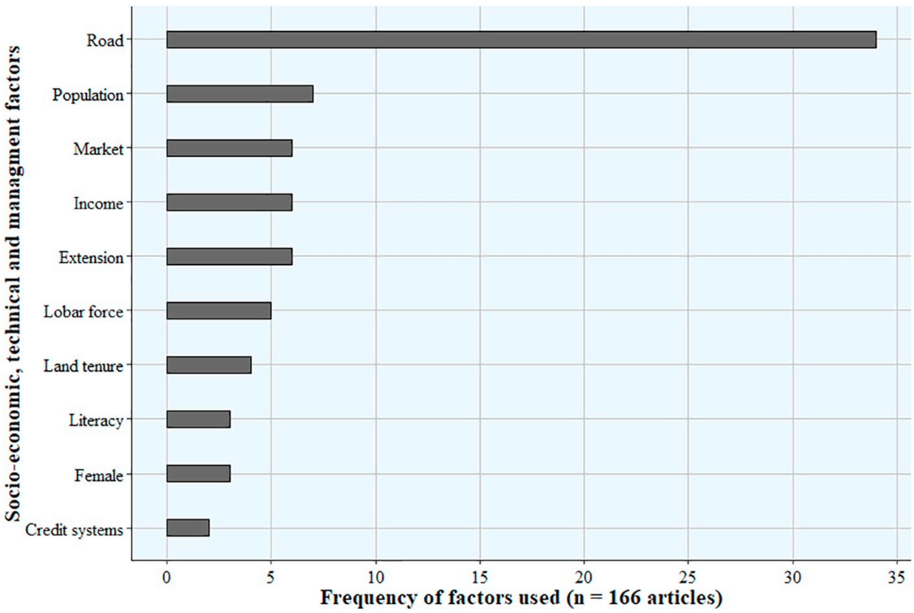

Fig. 9. The frequency of the top 10 socio-economic, technical and management factors used in ALSA. Road, road network, accessibility to road; Population, population density; Market, accessibility to market; Income, farmers income per given crop type; Extension, extension services; Labor force, labor force availability; Land tenure, access to agricultural land by farmers; Female, female participation in agricultural activities, female access to agricultural land; Credit systems, access to credit by small-scale farmers.

factors of soil and landscape), water availability in the root zone (8 factors for hydrology and irrigation) and socio-economic and technical requirements (11 factors). Not all ALSA studies reported in this article systematically include socio-economic analysis in the modeling.

3.4.1. Bio-physical requirements for ALSA

3.4.1.1. Climatic requirements. The cultivation of crops in a given area is highly linked to spatial and temporal variability of climatic conditions (Holzkämper et al., 2011). Crop growth and development are largely influenced by climate. It is therefore important to assess how climate is favorable for a given crop for the benefits of planners, land managers, farmers, and plant breeder (Caubel et al., 2015). A recent ALSA study for oil palm in Ghana shows that the main limiting factors for crop production is the water deficit while the current and predicted changes in climate suggest that growing conditions for oil palm in Ghana will become more favorable (Rhebergen et al., 2016). In the Philippines, rain-fed rice yields were strongly correlated to rainfall that seems to also influence planted area (Koide et al., 2013). Thus climatic influences are more complex (Iizumi & Ramankutty, 2015). Indeed, temperature impacts the lengths of the growing season in the temperate ecosystem while in the tropical warm ecosystem the growing season is determined by rainfall (Guerena, Ruiz-Ramos, Diaz-Ambrona, Conde, &

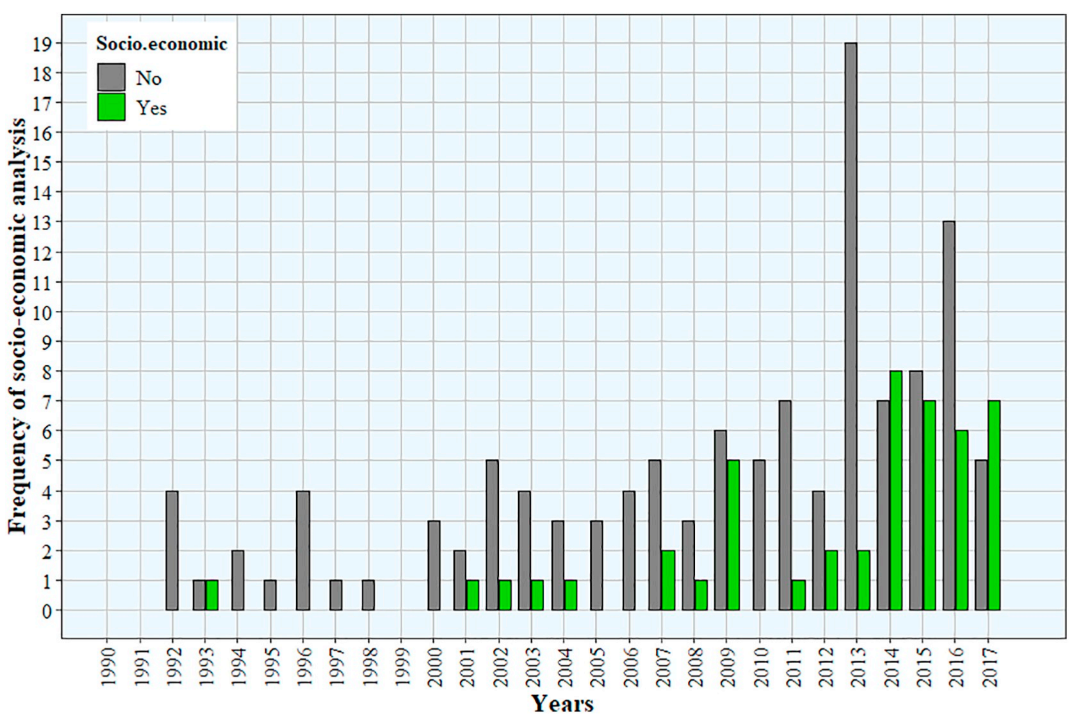

Fig. 10. Temporal evolution of socio-economic analysis in ALSA task.

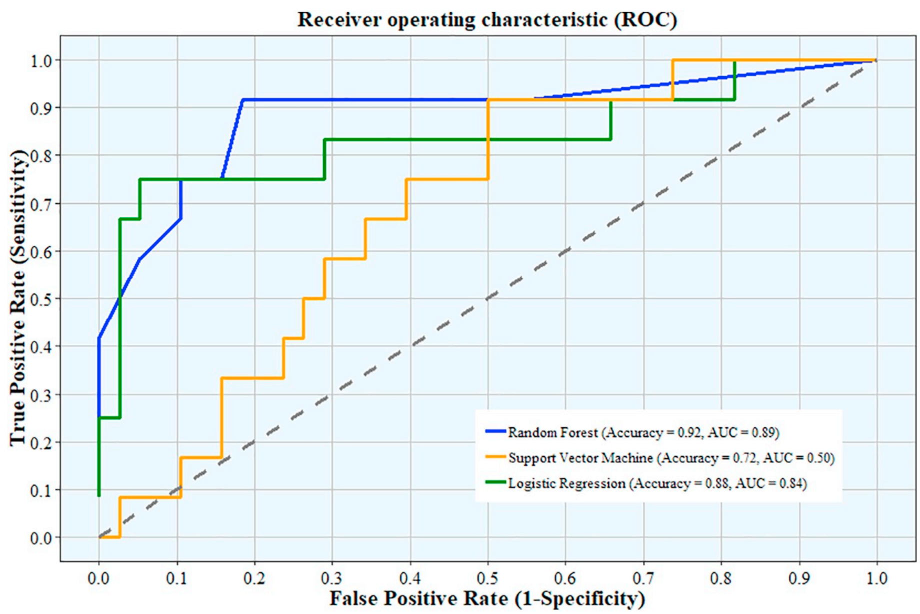

Fig. 11. The accuracy of machine learning methods in predicting including or not socio-economic factors in ALSA. The higher the area under the curve (close to one), the better the model. The 10-fold cross validation average accuracy for random forest gives 0.898. AUC, Area Under the Curve.

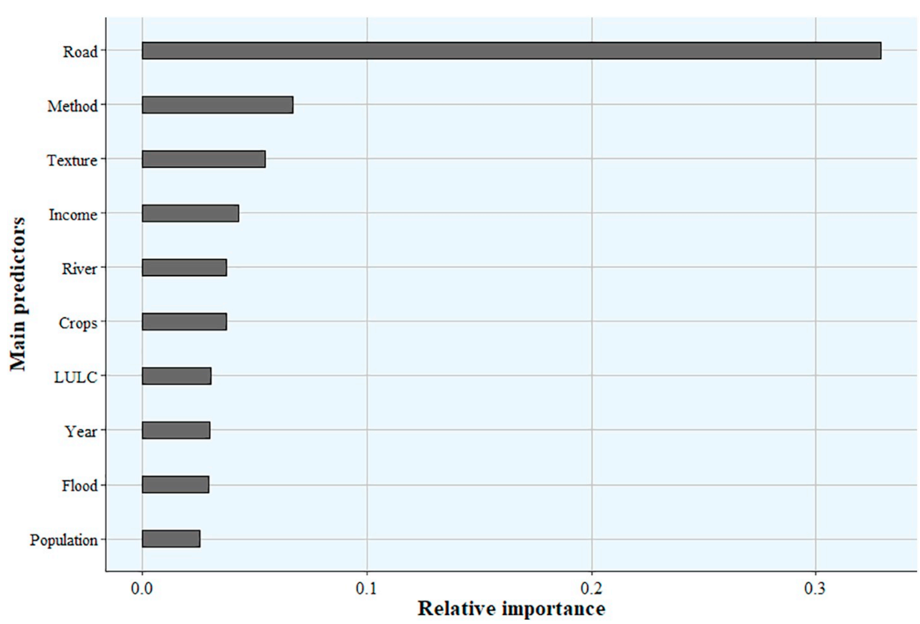

Fig. 12. Main predictors and their relative importance in modeling socio-economic analysis in ALSA. Notice the important role of the road as main predictors, but also the presence of predictors such as methods used, crop considered, the year of publication, the farmer's income, and population density.

Minguez, 2001). Furthermore, radiation plays a fundamental role in crops development (Westgate, Forcella, Reicosky, & Somsen, 1997). Frequently used climate factors in ALSA as reported in the papers reviewed for the present article are reported in Table 4. According to the objectives of the study and the type of crop considered, the choice of these factors may vary. It obviously not relevant to select parameters like a number of frost days or chill hours for tropical crops in sub-Saharan African. However, these factors seem import for the study of land suitability for saffron in Iran (Maleki, Kazemi, Siahmarguee, & Kamkar, 2017) and hazelnuts in Australia (Kidd, Webb, Malone, Minasny, & McBratney, 2015). The top 10 of the most used climatic factors is shown in Figure 6. Results revealed that precipitation, temperature, evapotranspiration, relative humidity, and solar ration are frequently included in ALSA.

3.4.1.2. Hydrology/irrigation requirements. The justification and choice of the hydrological and irrigation requirement for crops are reported in Table 5. The results of the ranking of the most used of these factors (see Figure 7) showed that water bodies, rivers and discharge, flooding hazards, irrigation water use, depth to water table, groundwater, soil wetness index, stream orders and considered as important for crops suitability analysis.

3.4.1.3. Soil parameters and landscape features. Bio-physical characteristics are variously factored in the ALSA as suggested by studies demonstrated in the previous section based not only on the

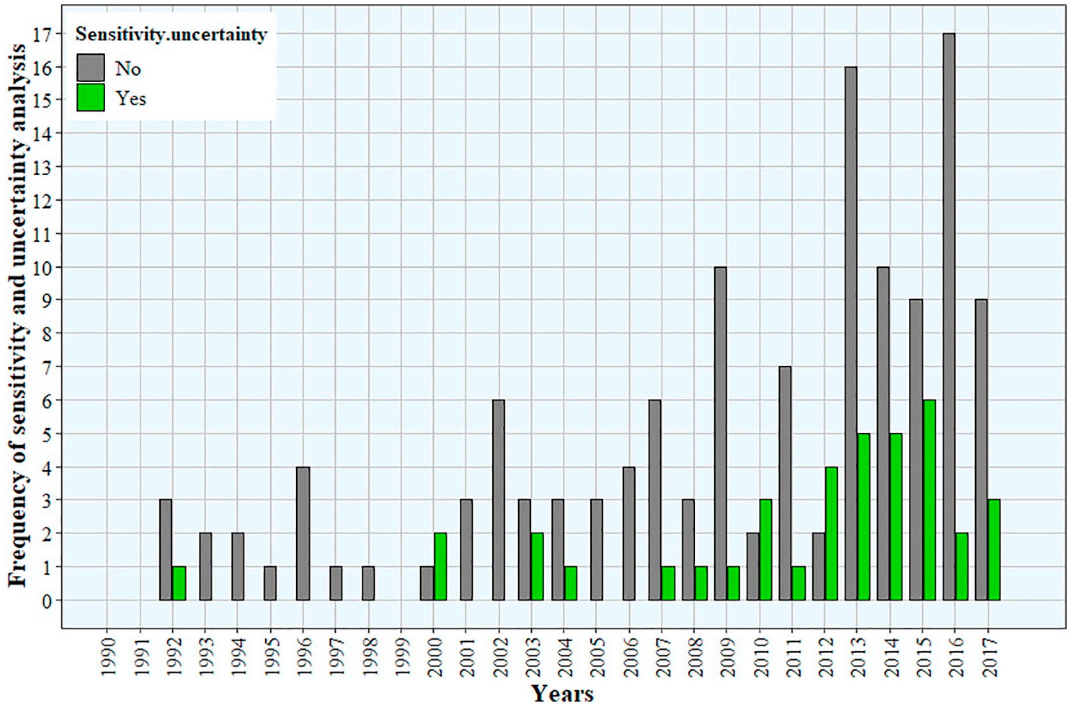

Fig. 13. Temporal evolution of sensitivity and uncertainty analysis in ALSA task.

objectives of the studies but also on data availability and the location of the study. For instance, physiographic components play a fundamental role in agriculture in the hilly zone (Zolekar & Bhagat, 2015) while the impact of topography is important for precision agriculture management, mainly in explaining yield variability (Kumhálová & Moudrý, 2014). The frequently used soil factors and landscapes attributes in ALSA are reported in Table 6 among which the top 10 are: slope, soil texture, soil effective depth, soil pH, land use land cover, soil drainage, organic carbon/organic matter, elevation, soil electrical conductivity or salinity, and soil type/soil group (see Figure 8). Crop suitability analysis frequently referred to matching tables developed by (FAO, 1976; Sys et al., 1991; Sys et al., 1993) or in some cases guideline for the selection of soil and climatic parameters specific to a region (Eliasson et al., 2010).

Soil data availability, the purity of soil map units and their quality for various uses alike LSA is always questioned (Safari, Esfandiarpour-boroujeni, Kamali, Salehi, & Bagheri-bodaghabadi, 2013). The empirical soil mapping for ALSA purposes is found that it is important for a soil survey to be conducted for more accurate results to be obtained (Kalogirou, 2002). This method can only be applied to small areas (Diallo et al., 2016) due to cost and time constraints. As an alternative, digital soil mapping methods have emerged with freely global data available but at coarse resolution (Batjes, 2009; Batjes, 2012; Hengl et al., 2015). These datasets are as accurate as the density of the training samples (Hengl et al., 2015) and exhibit discrepancies in ALSA results. (Avellan, Zabel, & Mauser, 2012) compared the ISRIC World Soil Information Center's World Inventory of Soil Emissions Potential 5 by 5 arc min Soil Map of the World (ISRIC-WISE 5by5 SMW) with the Harmonized World Soil Database (HWSD) in 0.5 arc min and the Kiel Climate Model (KCM) with the WorldClim model climate data for the assessment of biophysical crop suitability. Their results showed that the HWSD-based runs resulted in 10% less crop-suitable land than the ISRIC-WISE 5by5 SMW-based results. The KCM simulations predicted 1% less crop-suitable land than the WorldClim model. Their results demonstrate that discrepancies in crop suitable areas are largely due to the differences in the soil databases rather than to climate (Avellan et al., 2012). Results from this study also suggested that, for optimal outputs from agro-ecological models, the input databases have to deliver uniform and high-quality data on a detailed spatial scale. This can be achieved by resampling pixel size to a common scale (coarser or finer scale) using a majority filter for classified parameters and bilinear resampling for continuous data in a GIS environment. However, simply using smaller pixels does not necessarily result in more accurate results (Avellan et al., 2012).

3.4.2. Socio-economic and technical requirements for ALSA

The traditional approach to agricultural intensification considers crops suitability to be primarily based on soil and climate conditions. However, in sustainable intensification and conservation perspectives, this approach could be problematic due to the exploitation of many suitable forest areas leading to deforestation (Nijbroek & Andelman, 2015). Also, in getting a complete view of crop's ecosystems and factors that can explain and improve yield, inherent local socio-economic factors should be considered. In the light of the present work, this aspect has been often disregarded in most of the ALSA modeling (only 38% of the total reviewed article considered socio-economic factors) resulting in poor or incomplete outcomes. Indeed, evaluating multiple biophysical and socio-economic criteria across spatial scales is a complex process that is not only governed by the factors determining the biophysical land suitability, but it could depend on multiple drivers that should be considered under a spatial multi-scale analysis approach and requires a systematic approach which can be understood and adopted by agricultural investment planners and policy-makers (Martínez-Casasnovas, Klaasse, Nogués, & Ramos, 2008; Nijbroek & Andelman, 2015).

There are several reasons that could explain the weakness of the associations of crops with land suitability. One is related to the process through which farmers decide to sow one crop or another in a specific location (Martínez-Casasnovas et al., 2008). For instance, in a comparisons study of qualitative and quantitative methods to assess land suitability for barley–alfalfa–wheat-fallow crops rotation in Iran, produced very similar results for typical crops; however, for opportunist crops (such as alfalfa in the study area), the methods produced different results because such crops are more dependent on market conditions

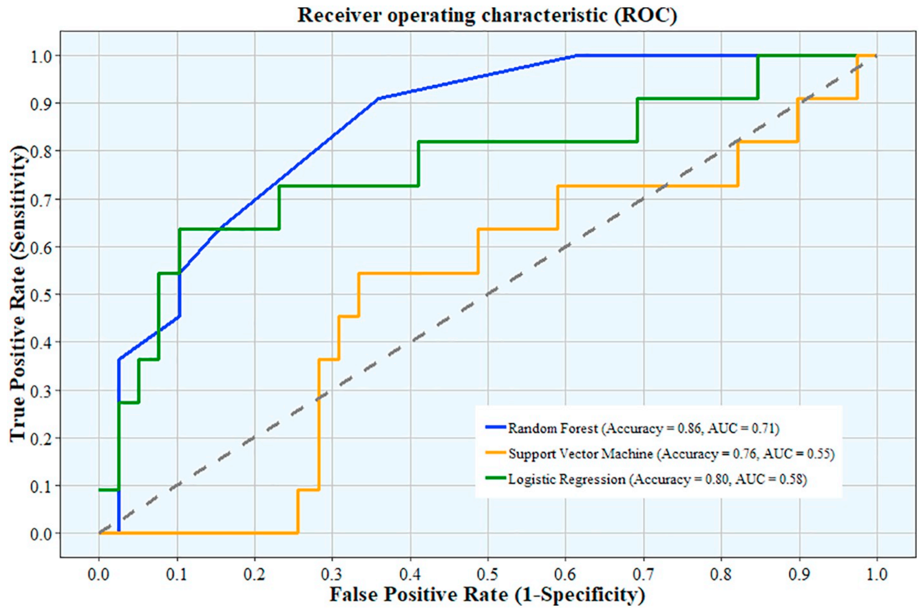

Fig. 14. Accuracy of machine learning methods in predicting the including or not uncertainty and sensitivity analysis in ALSA. The higher the area under the curve (close to one), the better the model. The 10-fold cross validation average accuracy for random forest gives 0.79. AUC, Area Under the Curve.

than on land characteristics (Branch, Co, & Town, 2015). Similarly, proximity to urban markets, or linkage to urban markets by efficient transportation networks, offers particular promise for more significant agricultural use of lowlands in West Africa (Dossou-Yovo, Baggie, Djagba, & Zwart, 2017; Erenstein, 2006) while female participation in economic activities or high literacy rate have proven high adaptive capacity in the context of climate change (Brandt et al., 2017; Eliasson et al., 2010). In Table 7, we depicted some socio-economic and technical factors often reported in ALSA modeling and their rank in Figure 9. The results showed that the road is the most used factor in considering socio-economic analysis in ALSA.

Although a limited number of studies have considered socio-economic factors in ALSA, results from our analysis showed that there is a growing interest in including this aspect in agricultural land use planning in these recent years (Figure 10). Furthermore, we applied machine learning methods to explain which variables contribute to the decision of the authors to include or not socio-economics factors in their analysis. To this end, three methods were used including random forest, logistic regression and support vector machine. Results showed that random forest outperformed the two other methods with the area under the curve of 0.89 followed by logistic regression (0.84) and support vector machine (0.5) (see Figure 11). Also, results from random forest

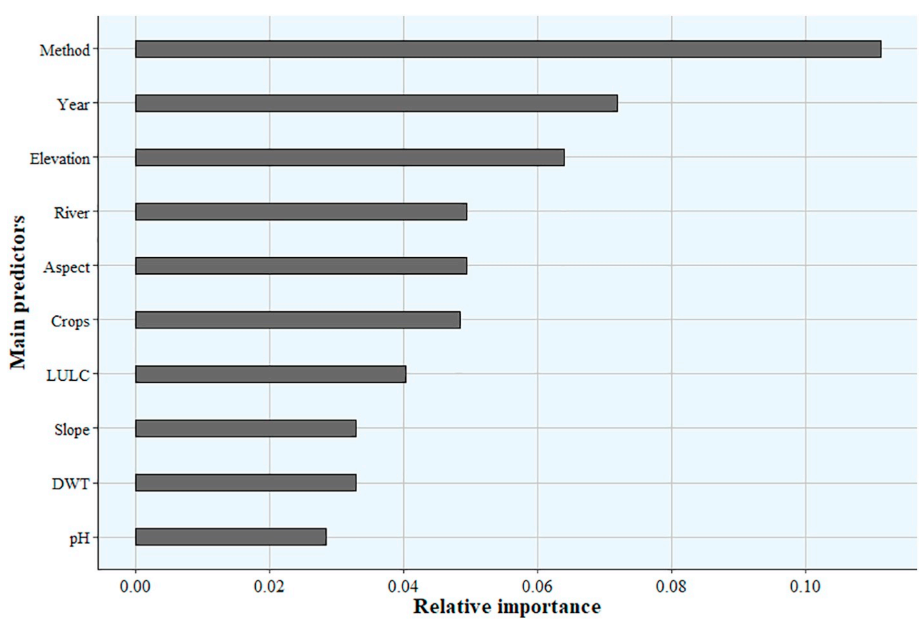

Fig. 15. Main predictors and their relative importance in modeling uncertainty and sensitivity analysis in ALSA. Although the relative importance of the predictors are weak (less than 20%) we can notice the important role of the choice of methods and the year of publication.

Table 8
Reported Correlation between crop yield and suitability class.

Crop	Parametric method					Maximum limiting/Boolean logic	GIS-MCA	Fuzzy set	FAO method	TOPSIS	Country	References
	Sys	storie	Square root	Geometric mean	based neural networks							
Rice						No significant correlation					Benin	Danvi et al. (2016)
Maize	0.90					0.81		0.96			China	Tang and Van Ranst (1992)
Rubber		0.81				0.19		0.89			Thailand	Van Ranst, Tang, Groenemans, and Sinthurahat (1996)
Sorghum			0.95								Ethiopia	Motuma et al. (2016)
Wheat			0.92								Ethiopia	Motuma et al. (2016)
rubber							0.95				Vietnam	Nguyen et al. (2015)
Olive		0.94									Iran	Lake et al. (2009)
alfalfa					0.93					0.88	Iran	Bagherzade and Gholizadeh (2016b)
sugar beet				0.87				0.94			Iran	Bagherzadeh and Gholizadeh (2016)
Soybean					0.61			0.51			Iran	Bagherzadeh et al. (2016)
switchgrass								0.6			USA	Feng et al. (2017)
Miscanthus								0.59			USA	Feng et al. (2017)
Maize	0.98										Iran	Rabati et al. (2012)
Sunflower	0.91										Iran	Rabati et al. (2012)

method have been used to rank the top 10 main predictors (see Figure 12). Results showed that road is the main predictors for socio-economic analysis in ALSA, confirming the ranking in Figure 9. In addition, the choice of methods used and the year of publication seem to play an important role in the socio-economic analysis (as depicted in Figure 12), while the inclusion of factors like farmers average income, the crop type and/or agricultural system considered as well as population density are among the main predictors.

3.5. Uncertainties and Sensitivity analysis in ALSA

The process of evaluating the suitability of agricultural fields is subjected to uncertainty which involves data and model uncertainty that range from measurement error to inherent variability, to instability, to conceptual ambiguity, to over-abstraction, or to simple ignorance of important factors (Kurtener et al., 2008) and uncertainties due to processes that are included in the model, but their occurrences are unknown to the modeler; and uncertainties due to processes unknown to the modeler and not included in the model. In model building, uncertainty analysis (UA) and sensitivity analysis (SA) are essential requirements (Crosetto, Tarantola, & Saltelli, 2000). While SA represents the effects of input factors and assumptions on the model outputs, UA is related to the study of the resultant effects of known limitations or errors associated with the model itself. Subsequently, the SA procedures can help reduce uncertainty in MCE problems and the stability of its outputs by illustrating the impact of introducing small changes to a specific input parameters on evaluation outcomes (Crosetto et al., 2000).

Although SA and UA are fully justified, few articles have reported there applications and visualization of model predictions of land suitability for regional agricultural production (Benke & Pelizaro, 2010). From our analysis, only 30% of the studies (38 articles out of a total of 166) included UA and SA in their modeling process. This might be partly due to the fact that hardly any GIS software currently in use can present the user with information about the confidence limits that should be associated with the results of an analysis (Crosetto et al., 2000). GIS methods facilitate the storage, manipulation, analysis, and visualization of spatial data but there are several problems associated with implementing the MCE methods in GIS.

First, the spatial data have errors due to measurement, digitization, or interpolation. The input data to the GIS-MCE procedures usually have the property of inaccuracy, imprecision, and ambiguity. The sources of error can be classified into categorical, temporal, and spatial types (Campbell et al., 1992). Categorical error occurs on the interpretation stage of the raw data (e.g., remote sensing data) or when a wrong classification scheme is used to rank the data. Temporal errors may occur when data are being assembled (in overlay type operation) but where not collected during the same time period and higher-level spatial analytic manipulations may also be subjected to spatial errors. GIS-MCE methods typically assume that the input data are precise and accurate.

The second problem is related to the standardization of non-commensurate criteria. There are many different standardization methods that can be used in the GIS-based multi-attribute analysis. To this end, it is important to note that different standardization methods may lead to different land-use suitability patterns (Malczewski, 2004). Third, given the wide variety of MCE rules, there is a question which of the methods is the best one to be used in a particular situation. This is a largely unsolved issue in decision analysis (Malczewski, 2004).

Attempts to error analysis in GIS have used probability modeling (Crosetto et al., 2000). According to Hartkamp, White, and G. H. (1999), this approach is problematic due to the variety of possible spatial data processing procedures and the rigorous requirements of probabilistic data gathering. In ALSA, criteria weights determined from pairwise comparisons are often the greatest contributor to the uncertainties in the AHP-based MCE (Chen, Yu, & Khan, 2013). Recent

sensitivity analysis in the field has adopted One-factor-At-a-Time (OAT) method along with the AHP technique (Chen et al., 2013; Chen, Khan, & Paydar, 2010; Xu & Zhang, 2013) and fuzzy logic (Feng et al., 2017b). There are three main reasons for the adoption of the OAT method (Chen et al., 2013): (1) the OAT is easy to implement; (2) The characteristics of the AHP (that compare and rank 2 factors at time through a matrix), satisfies the independence requirement of the OAT; and (3) the results generated from the OAT are easy to understand due to one at time effect on complex output. Assessing land suitability is inherently a subjective process that is often based on classified environmental variables whose spatial boundaries assume a spatial homogeneity that is unrealistic when compared to what occurs on the landscape (Joss, Hall, Sidders, & Keddy, 2008). Fuzzy sets theory and fuzzy logic incorporate and processes variation in expert judgment while providing a mechanism to handle spatial uncertainty that results in more continuous and realistic classifications of land suitability(Davidson et al., 1996; Baja et al., 2002; Kurtener et al., 2008; Zoccali et al., 2017).

Alike socio-economic analysis, uncertainty, and sensitivity analysis in ALSA have been mostly adopted in the last decade as shown in Figure 13. Also, machine learning methods were used to model the mains elements that explain the inclusion of the uncertainty and sensitivity analysis in ALSA based on the random forest, logistic regression and support vector machine algorithms. Results showed that random forest performed better than other methods (see Figure 14). In addition, results from random forest showed that the method used and the year of publications are the most important variables that explain the inclusion of uncertainty and sensitivity analysis in the modeling process (Figure 15).

3.6. Validation of agricultural land suitability analysis

Validation of ALSA models and/or results are not always easy and there are no definite methods for this assignment. Different approaches have been reported including multiple models' application, ground truth, and correlation of land suitability indices against crop yield. In the case of multiple model application, validation can be performed using the Kappa coefficient as a measure of agreement between the methods (El Baroudi, 2016).

Several studies on the suitability modeling adopted the correlation between crop yield and the suitability class as a measure of validation of their model (Table 8). In such an analysis, most of the correlation coefficient was higher than 0.5. In other cases, the authors reported no significant correlation although their results agreed on ground truth through fieldwork. For instance (Danvi et al., 2016) reported rice yields distribution and farmers interview as validation method their suitability analysis. Although special explicit maps show confidence in the suitability distribution, lack of management practices was reported to results in low yield, which in turn, showed poor agreement with suitability classes. This is leaving the issue of validation unsolved and therefore questioning the relevance of the methodology. A good proxy, however, could be the use of the cultivated area for validation. This is because agricultural production is essentially extensive with low inputs in SSA and farmers will likely cultivate large area where the land is more suitable.

In addition, remote sensing data has been used to evaluate land suitability models. For instance, a forage maize land suitability study was conducted using comparative land evaluation approaches (Manna et al., 2009). In assessing the predictive performance, a specific method to successfully discriminate areas with different forage maize suitability, (Manna et al., 2009) conducted for each of their suitability model a comparison of model estimates of forage maize biomass with remotely sensed data. Thus, the NDVI-maize green biomass production data were compared to maize plants total dry biomass with a positive correlation of 0.832.

4. Conclusions and outlooks for integration of climate change analysis in ALSA

This work reviews the state-of-the-art and future perspectives of Agricultural Land Suitability Analysis (ALSA). The major themes in the SDG2 are "end hunger", "achieve food security" and promote sustainable agriculture. Food security can be achieved through sustainable agriculture which in turn can end hunger. Climate change, however, is putting more pressure on agricultural lands with disasters like drought and flood. A profound change of global food and farming systems is necessary to continue feeding growing population up to the end of 2050 and beyond. Agricultural Land Suitability Analysis attempts to evaluate suitable crop land, hence a means of promoting sustainable agriculture and food security to end hunger. However, ALSA has to be implemented with full awareness and account of current and future climate change impacts. Thus, ALSA under climate change is a necessary requirement for sustainable agriculture and food security. We recommend based on the review of the current ALSA method towards sustainable agriculture and food security the following:

- Climate change impacts on current and future cropping area and production should be incorporated into ALSA methods by including climate change scenarios in their simulation. Research in this area is quite limited as revealed by our review. A general limitation is that individual climate models have poor resolution and it is required in specific cases to combine multiple GCM to come up with good climate change predictions. The coarser resolution of GCMs makes them unsuitable for impact studies in general and ALSA for that matter. A robust mechanism such as statistical downscaling techniques can be employed in ALSA models to downscale the output of GCM using local conditions. A list of climate parameters can be made available for users and experts to select climate parameters that drive the local climate. Even though this approach will still be subjective to experts' choice, it will prevent using the same parameter for different climate regions and will be advantageous to experts who understand the local climate.
- Crop models are usually designed for specific crops and contain specific crop coefficients/indices, biophysical, socio-economic and phenological data for the specific location. Creation of a global open database where individuals in specific locations identified by longitude and latitude can perform and upload information can increase the use of crop models. From this database, developers can test the performance of their models for specific locations and correct limitations they identify. Uncertainty analysis and sensitivity analysis can be performed on the models in addition to calibration and validation of the models. This will increase the performance and application of crop models in general. In our view, one of the best approaches to sustainable agriculture and food security is the use of local information to simulate, correct and improve the prediction power of current ALSA crop models. Global food security will be achieved if local food security is achieved through sustainable agriculture.
- Owing to the limitations related to crop models and usual land evaluation methods, qualitative and quantitative approaches must be integrated into a unique ALSA system (Hybrid Land Evaluation System - HLES) to improve the land evaluation while providing support tools to stakeholders for better adaptation to climate change.

Acknowledgments

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Appendix 1: ALSA database

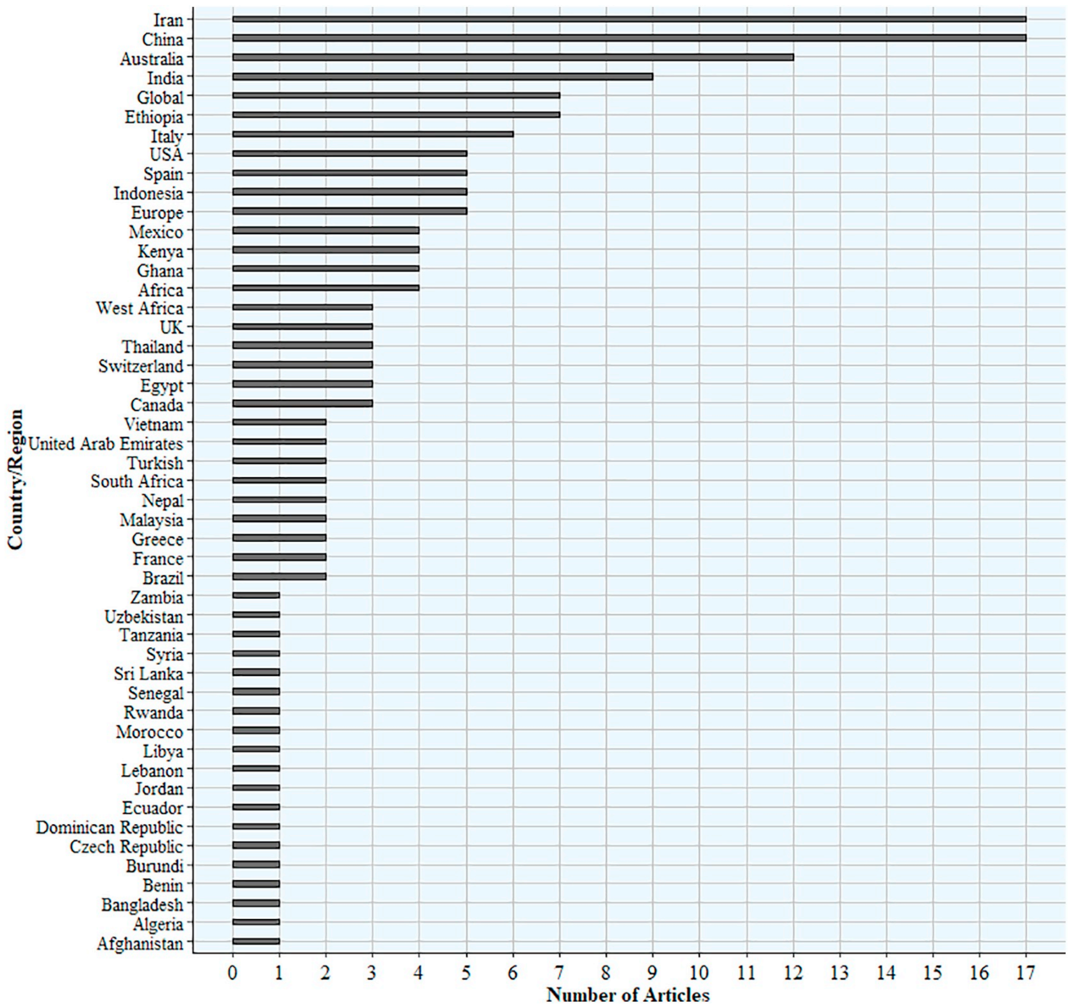

Fig. A1. Number of ALSA publications per country from 1990 to 2017.

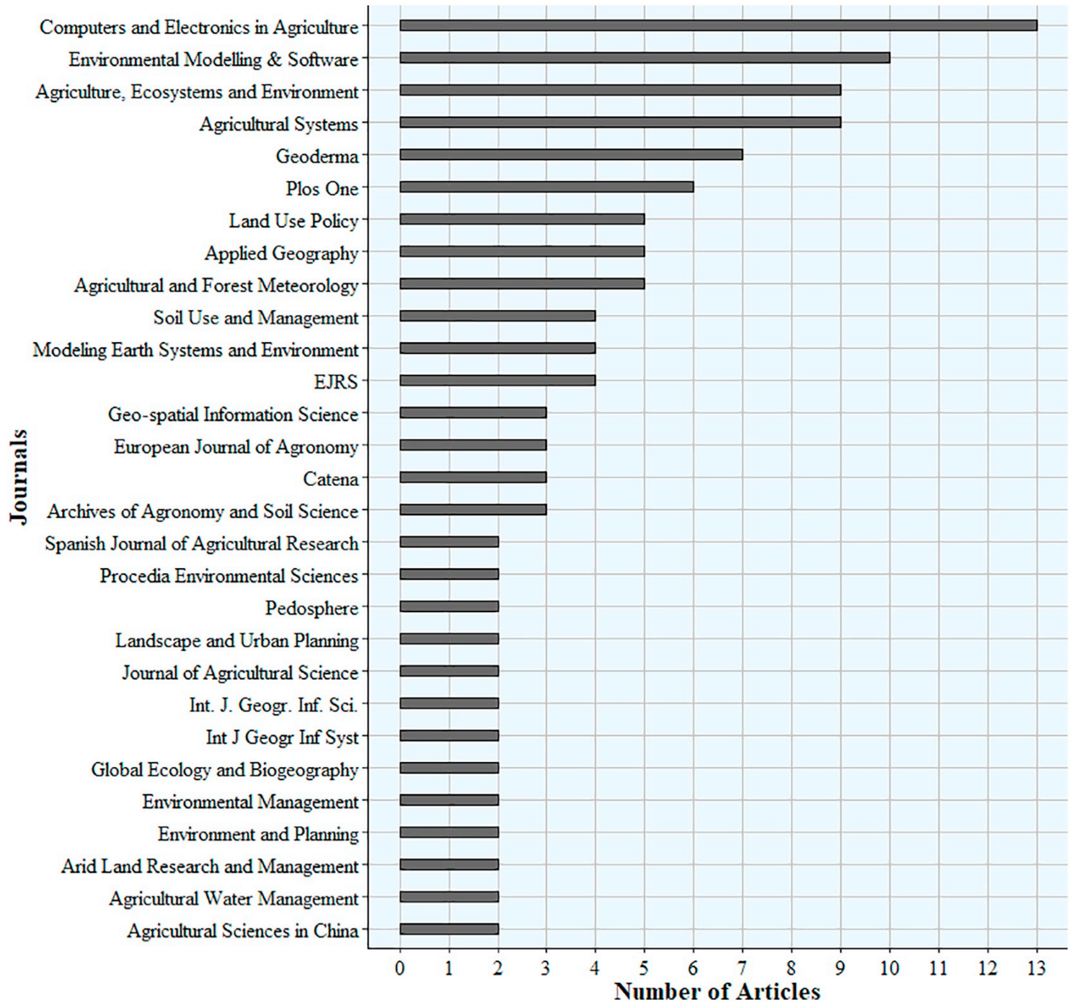

Fig. A2. Number of publications per journal (here we show only journals that have 2 or more papers reviewed).

Table A1
Applications of the traditional methods to ALSA.

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
Baroudy (2016)	Spatial model for land suitability assessment	N-P-K, Zn, D, Tex, Dep, Topo, SS, HP, HC, WHC, EC, ESP, CaCO3 and pH	Parametric	Wheat	No
Danvi et al. (2016)	Determine suitable areas for rice production	P, T, RH, R, Flooding, D, Dep, CEC, BSP, pH, OC	Boolean Logic, Maximum Limiting factor	Rice	No
Masoud, Forkuor, Namara, and Ofori (2013)	Most suitable areas for inland valley rice cultivation	P, stream order, discharge, S, fertility, LGP, PHT, Land tenure, roads, markets, credit systems, incentive benefit, pH, N, OC, , EC, CEC, BSP	WLC	Rice	No
Kuria, Ngari, and Waithaka (2011)	Suitability for rice growing	landforms, LULC, Tex, ESP	WO	Rice	No
Gumma et al., 2009	Suitable areas for inland valley, wetland rice cultivation:	P, ET, LGP, discharge, stream order, slope, vegetation, soil type, Dep, fertility, socio-economic, technical and eco-environmental	WLC	Rice	No
Motuma et al. (2016)	Land suitability analysis	Dep, Text, OC, D, Soil type, S, T, and P	Square Root, WLC	Wheat, sorghum	No
Naughton, Lovett, & Mihelcic, 2015	Suitability model	LULC, T, P, H, fire, NDVI, soil-type and D	Multiplicative, Additive	shea	No
Behzad et al. (2009)	Evaluate and compare land suitability for principal crops	RH, T, SR, S, Tex, % CaSO4, EC, CEC, ESP, Drain	Storie, Square Root	wheat, alfalfa, barley and maize	No
Rhebergen et al., 2016	land suitability for oil palm production	SR, P, T, S, PET, AWC, Tex, SG, silt, clay,	WO	Palm oil	Yes

(continued on next page)

Table A1 (*continued*)

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
D'Angelo et al. (2000)	Assessment of agro-silvo-pastoral systems environmental impact in marginal Mediterranean areas	H, S, As, LULC, SS, DM, Frost, Flood, Dep, Tex, BSP, WHC, structure stability	WLC	Agricultural system	No
Munene, Chabala, and Mweetwa (2017)	Identifying suitable land for soybean production	Tex, OC, Phosphorus, pH, Drain, S, H, Roads	WLC	Soybean	No
Seyedmohammadi, Esmaeelnejad, and Ramezanpour (2016)	Evaluate and compare land suitability for surface, sprinkler and drip irrigation	Dep, Text, EC, pH, OM, CaCO3, CEC, S	Square Root, Sorie	Irrigated agriculture	No
Nzeyimana et al. (2014)	To analyze the spatial distribution of potential production zones for Arabica coffee the current productivity	H, P, T, SG and S	WO	Arabica coffee	No
Abdelfattah (2013)	Land suitability for irrigated agriculture	SG, coarse fragments, Tex, EC, Dep, HP, DWT, %CaSO4, T, S, H, IWU	FAO method	irrigated agriculture	No
Albaji, Golabi, Nasab, and Jahanshahi (2014)	Compare different irrigation methods	SG, Dep, Text, EC, pH, OM, CEC, CaCO3, T, RH, PET, P, Drain, S	Sys, Storie	surface, sprinkler and drip irrigation systems	No
Al-Yamani et al. (2013)	Land suitability study	Tex, EC, DWT, HP, CaSO4, H, S	Limiting method, WLC	halophytic bioenergy crop	No
Baniya et al. (2013)	Categorize available land area in the range of suitability ratings	H, T, RH, P, Asp, Tex, Fertility, Irrigation, pH, S, Dep, PET, LULC, SG	FAO method	cardamom	No
Diallo et al. (2016)	Suitability of soils for the cultivation of upland rice in a peri-urban wetland	P, T, RH, Wind, SH, PET, S, Drain, Coarse fragment, Dep, Tex, clay, silt, sand, CEC, OM, BSP, EC, ESP, pH, N, K, Ca, Mg, Soil thickness, Soil consistency, soil color, Transition, Soil condition, DM	Storie, PCA	rice, cassava and groundnut	No
Qin and Jixian (2002)	Guidelines of land use planning	SG, Dep, Fertility, Tex, S, Disaster, P, Road, River	Parametric	Agriculture land use planning	No
Ismail, Abdel Ghaffar, & Azzam, 2012	GIS application for analyzing the spatial distributions of physical and chemical properties of the study soils to produce land utilization types of irrigation	S, Dep, SE, Drain, infiltration rate, AWHC, SS, stones in surface horizon, rock outcrop, EC, ESP and CaCO3	Multiplying	land utilization types of irrigation	No
Kamkar, Dorri, and Da Silva (2014)	Perform land suitability assessments	P and T, As, H, S, Tex, pH, EC	Computer Overlay	canola, soybean	No
Elsheikh et al. (2013)	Intelligent system for assessing land suitability for different types of crops	P, DM, pH, Dep, OM, CEC, Clay, BSP, Coase fragment, Dep, Tex, Oxygen availability, S, Drain, LULC, Flood	FAO-SYS	mango, banana, papaya, citrus, and guava	No
Lake, Mehrjardi, Akbarzadeh, and Ramezanpour (2009)	To evaluate the qualitative and quantitative land suitability	Dep, Silt, Sand, Clay, Gravel, pH, EC, CaSO4, OC, CEC, BSP, ESP	Square Root, Sorie, FAO	Olive plant	No
Martínez-Casasnovas et al. (2008)	Biophysical land suitability compared to different crop frequency parameters	Fertility, Flood risk, LGP, hailstorms, winds, location, mechanization potential, oxygen availability, pests and diseases, pre- and post-harvest management, Dep, EC, ESP, trafficability and ploughing, SR, T, IWU	FAO, Statistics	Alfalfa, winter cereals, maize, rice, sunflower	No
Hennebert, Tessens, Tourenne, and Delvaux (1996)	Land evaluation	S, Drain, H, Dep, SS, Tex, CEC, pH, BSP, OC, LGP, P, T, RH, SH, LULC	Sys	Wheat, pea bean, maize, potato	No
Abdelrahman, Natarajan, and Hegde (2016)	Develop a GIS based approach for land use Suitability assessment	P, S, Tex, LULC, Dep, CaCO3, CaSO4, ESP, pH, CEC, OC, BSP, Drain, SE, P, T, Coarse fragment	Land capability and Geo-statistics	Cotton, Finger millet, Groundnut, rice, sorghum, banana, cashew	No
Safari et al. (2013)	Compare geostatistical and conventional soil mapping methods for main irrigated crops	Clay, sand, coarse fragments, pH, EC, CaCO3, SAR, Tex, P, T, RH, SR, Drain, Flood, DWT, SS, Coarse fragment, Dep, CaSO4, BSP, CEC	Geo-statistics	wheat, sugar beet, potato and alfalfa	No
Bojórquez-Tapia et al. (2001)	GIS-based multivariate application for land suitability assessment	SG, Distance to mangrove, to agriculture and cattle ranching, to mayor roads, Brackish water, Riparian zones, Flood free zones, Natural cover, coastal lagoons and flood prone zones	Multivariate statistics, WLC, PCA	Shrimp farming	No
Bydekerke et al. (1998)	crop specific land suitability assessment	SG, Tex, Dep, CEC, OM, P, T, LGP, RH	Expert Knowledge, FAO method	Cherimoya	No
Saroinsong et al., 2007	A multi-criteria analysis approach to agricultural landscape planning	SR, T, P, RH, Drain, Text, Dep, ESP, pH, Flood, SE, LULC, H, S	USLE, FAO method	Agricultural system	No
Nijbroek and Andelman (2015)	Suitability for agricultural intensification at the regional scale	Yield, Protected areas, Forest cover, Annual water balance, Population and infrastructure, Living standard measurement study, integrated survey of agriculture, OM, Fertility, SG, extension services, IWU	Stepwise multivariate regression, WLC	maize, sorghum and pearl millet	No
Sani et al. (2016)	To assess ecological land suitability	LULC, IWU, Tex, pH, Fertility, SE, H, P, T, S, As, SG	WLC	Forestry	No

(*continued on next page*)

Table A1 (*continued*)

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
Fontes, Fontes, & Carneiro, 2009	Land suitability	Fertility, PET, P, SS and restraining of agricultural mechanization, Technical assistance, Fertilizers/ correctives, Pest and disease control, Soil conservation practices, IWU, Electric power, LULC	WLC	Agricultural system	No
Bandyopadhyay, Jaiswal, Hegde, and Jayaraman (2009)	Land suitability potential evaluation in a watershed	LULC, SG, S, OC, Dep, Tex, SE, Drain, pH	WLC	Agriculture	No
Chen et al. (2013)	Sustainable land use planning	S, As, SG, H, LULC, Income	Qualitative approach	Maize, Pear millet, Foxtail millet, Potato, apple, vegetable	No
Sarkar, Ghosh, and Banik (2014)	Multi-criteria land evaluation for analyzing land suitability	Dep, Tex, Drain, pH, P, S, LULC	WO	wheat	No
Schiefer, Lair, and Blum (2016)	Identify and localize arable soils with a high potential of recovery after disturbances in Europe	OC, CEC, Clay, Silt, pH, Dep, S, SG	Classification based on threshold	Sustainable intensification in agriculture	No
Shalaby, Ouma, and Tateishi (2006)	Develop a land suitability assessment	T, S, Flood, Drain, Tex, Coarse fragments, Dep, CaCO3, CaSO4, EC, ESP, DWT	Storie and square root	guava, olive and date palm	No
Wang, Lu, Fang, and Shen (2007)	Development of the current grain-for-green policy mainly based on a zonal detailed cropland suitability	T, S, SE, IWU, Drain, Dep, Tex, ESP	FAO method	cropland suitability	No
Littleboy, Smith, and Bryant (1996)	Comparison between a qualitative and quantitative evaluation	P, T, PET, SR, SG, WHC, S, H, LGP, infiltration, Drain, SE	Qualitative and quantitative with a cropping systems model called PERFECT	Wheat	No
Cools et al. (2003)	integrate the knowledge of both farmers and land resource experts in order to promote adoption of new land use systems	S, Flood, Drain, Tex, Coarse fragments, Dep, CaCO3, CaSO4, CEC, BSP, pH, OC, EC, ESP	Participatory mapping, FAO-Sys method	Olive trees, Chickpea, Barley, Wheat, Lentil, grape	No
Ryder (2003)	This paper examines peasant agriculture and awareness of soil	pH, CEC, ESP, Drain, Dep	point score analysis, Chi test of statistical association	Coffee, beans, grazing, pigeon peas, garlic, and rice	No
Zurayk et al. (2001)	The study aimed at supporting sustainable land management by carrying out a land capability classification and a land use analysis	Tex, EC, pH, OM, CaCO3, SS, S, LULC	Land capability assessment, participatory rural appraisal	Agricultural system	No
Ziadat (2007)	To explore the accuracy of land suitability classifications derived from predicted soil attributes versus those derived from traditional soil maps	Dep, S, WHC, SE; erosion wind, rock, boulder, stone, gravel	Multiple linear regression models	Field crops and range crops	No
Jones et al. (1998)	Identify and describe a set of common biophysical criteria capable of indicating the overall suitability of land for agriculture	T, Heat stress, D, Tex, stoniness, Dep, Soil moisture, S	Bio-physical classification based on threshold	Agricultural land use	No
Bagheri Bodaghabadi et al. (2015)	Land classification for irrigation	SG, Dep, Sand, Silt, Clay, Gravel, CCE, OM, Tex, pH, EC	AEZ, Maximum limiting factor	Wheat, Barley, Alfalfa	No
Teixeira et al. (2013)	Spatial assessment of heat stress risk	Max and min T, LULC, S, H	GAEZ	Wheat, maize, rice and soybean	Yes
Fischer et al. (2005)	Impacts of climate change on agro-ecosystems	SG, H, S, Min and Max T, P, RH, vapour pressure deficit, LULC	GAEZ	wheat, maize and other coarse grains	Yes
Fischer and Sun (2001)	Analyzing and projecting regional land use in China.	T, P, SH, H, S, SG, LULC	AEZ	Agricultural land use system	Yes

List of abbreviations: Temperature (T), dry month/ length of dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), available nutrient/Fertility (total N, P2O5, K2O), Slope (S), Aspect (As), Elevation (H), land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Depth to water-table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity(EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% CaSO4), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC).

Table A2
Case studies of AHP/ANP, OWA, LSP and ELECTRE Tri methods to ALSA.

Reference	Main purpose of the study	Major Criteria considered	Model/ Method	Crop/ Agricultural systems	Climate change issue considered (Yes/No)
Yalew, Van Griensven, and Van Der Zaag (2016)	A web-based framework for ALSA	River, LULC, SG, S, Roads, H, WHC, SS, Dep	AHP	Agricultural land use Classification	No
Kihoro et al. (2013)	Suitability map for rice crop	RH, T, Tex, pH, Drain, S	AHP	Rice	No
Akıncı et al. (2013)	Suitable lands for agricultural use	SG, LULC, S, H, SE, Wetness, Food, Water bodies, Dep, SS,	AHP	Agricultural land use Suitability	No
Ceballos-Silva and Lopez-Blanco (2003)	Delineate the suitable areas for the maize and potato crops	LULC, max and min T, P, PET, Tex, pH, Dep, S, H	AHP, PCA	Maize, potato	No
Feizizadeh and Blaschke (2013)	Capacity of a land unit to support a specific land use	H, S, Aps, Fertility, pH, T, P, GW	AHP	Irrigated and dry-farm agriculture	No
Romano et al. (2015)	MCDA to evaluate the potential of a rural coastal area	S, Asp, roads, river, LULC	AHP, OWA, Boolean	Restoration of manor farms	No
Zabihi et al. (2015)	Land suitability analysis	LULC, P, T, RH, GDD, SH, H, As, S, roads, Population, River	ANP	Citrus	No
Zolekar and Bhagat (2015)	Land suitability analysis in hilly zone	S, LULC, Dep, SE, SM, WHC, Tex, pH, OC, N-P-K	AHP	Agriculture	No
Cengiz and Akbulak (2009)	Land-use suitability analysis	Dep, LULC, SE, S, As, Water Bodies, road, SG	AHP	Agriculture	No
Zhang et al. (2015)	land suitability for flue-cured tobacco production	T, P, SH, RH, Cl, pH, OM, N-P-K, Ca, Mg, H, S, SG	AHP and Fuzzy	Tobacco	No
Benke and Pelizaro (2010)	Application and importance of uncertainty analysis in LSA	pH, WHC, Coarse fragment, Dep, tex, EC, Drain, As, T, P	AHP	Ryegrass, Winter Wheat	No
Chen, Yu, and Khan (2010)	Spatial dimension of multi-criteria weight for the expansion or retirement of the irrigated land use	HC, S, Tex, DTW, EC	AHP, OAT	Irrigated cropping, land use	No
Mishra et al. (2015)	Suitable zones in the state for the development of the organic farming	Drain, road, SG, LULC, S	AHP	Organic farminng	No
Chandio, Matori, Yusof, Talpur, and Aminu (2014)	Sustainable land suitability model for hillside development	Road, As, LULC, H, S, Water bodies	AHP	Include agriculture	No
Chen et al. (2013)	Criteria weight sensitivity in OAT-AHP	HC, S, Tex, DTW, EC	AHP	Irrigated croplands	No
Deng et al. (2014)	Calculate the suitability of land for alfalfa cultivation	P, T, RH, S, H, Dep, pH, OM, Sand, Distance to city, road, river, labor force	AHP, Fuzzy	alfalfa	No
Alkimim, Sparovek, and Clarke (2015)	Identify and map the currently cultivated pasture lands that are most suitable for conversion to sugarcane	SG, P, T, H, LULC, Infrastructure, population, Literacy, Labor force	AHP	sugarcane	No
Dadhich, Patel, and Kalubarme (2017)	Crop land suitability for wheat	Tex, pH, ESP, EC, Drain, N-P-K, LULC, S, GW	AHP, WO	wheat	No
Yalew, Van Griensven, Mul, and Van Der Zaag (2016)	Agricultural land use suitability	H, S, SG, Dep, SS, WHC, Towns, Roads, River/water, Protected areas, LULC	AHP, WO	Agricultural system	No
Yi and Wang (2013)	To determine which land use is best suited to the revegetation program by assessing the land suitability	LULC, S, H, OM, N-P-K, BD, Tex, WHC	AHP	Farmland/vegetation restoration	No
Chen et al. (2013)	Framework of multi-criteria assessments	Waterlogging, DWT, WHC, EC, GW, pH, Fertility, S, SS, Tex, HP, BT, ESP	Fzzy, OWA, AHP	Irrigated pasture	No
Brandt et al. (2017)	Develop a decision support framework for the spatially-explicit targeting of climate smart agriculture, and suitable CSA practices.	P, OC, Percentage of households with access to safe water, Literacy, Female participation in economic activities, Connectivity through transport, infrastructure	AHP, WLC	Climate smart agriculture	Yes
Worqlul et al. (2017)	Estimate of the potential suitable land for groundwater irrigation	LULC, SG, H, Population density, Road network, PET, P, Potential borehole yield, DWT, storage, recharge, S	AHP	Agricultural irrigation	No
Elaalem (2013)	Land suitability evaluations	WHC, Dep, Infiltration, Tex, ESP, P, T, SE, S	Fuzzy, AHP, Parametric	Olive	No
García et al. (2014)	Evaluate optimal locations of new agri-food warehouses	Accessibility to the area, distance, cost, security of the region, local acceptance of the company, and its needs	AHP	Agribusiness (banana distribution warehouse)	No
Hood, Cechet, Hossain, and Sheffield (2006)	Potential for growing Cool Climate Grapes	TDD, P, Frost, S, As, Drain, pH, ESP, Dep, Tex, EC	AHP, WLC	Grapes, pasture, and blue gum	Yes
Bo et al. (2012)	Evaluate the suitability of tea crop	T, Frost, RH, S, As, H, SG, Tex	AHP, GRA	Tea	

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Table A2 (*continued*)

Reference	Main purpose of the study	Major Criteria considered	Model/ Method	Crop/ Agricultural systems	Climate change issue considered (Yes/No)
Maleki et al. (2017)	Model to assess land suitability for cultivation of saffron	P, T, SH, frost days, RH, S, As, H, EC, pH, Tex	AHP, WO	Saffron	No
Malczewski et al. (2003)	Present the parameterized-OWA method applied to management situation	GW, city well heads, SE, Wetlands, Forest interior to water, Proximity to natural ears, LULC, Property ownership	OWA	Watershed management	No
Xu and Zhang (2013)	Framework that incorporates the spatial configuration information from sensitivity analysis for MCE	Tex, Dep, OM, sand dune waviness, SE, Drain, DWT	AHP, OAT, WLC	Wheat	No
Mendas and Delali (2012)	Propose a conceptual and methodological framework for the combination of GIS and multi-criteria methods	Water reserve easily utilizable, Drain, Permeability, pH, EC, Active limestone, CEC, Tex, Dep, S, availability of labor, proximity (roads)	ELECTRE Tri	Agricultural system	No
La Rosa, Barbarossa, Privitera, and Martinico (2014)	Characterization of new forms of urban agriculture	Farmlands, abandoned farmlands, woods and shrubs, bare Soils	Multi-Attribute model	Urban agriculture	No
Montgomery et al. (2016)	Agricultural suitability	SG, To, climatic, economic, land use and accessibility attributes	Logic Scoring of Preference (LSP)	Agricultural systems	No
Montgomery et al. (2016)	GIS-based Logic Scoring of Preference (LSP) method as an improved method of MCE	SG, P, T, Road, LULC, Economic, S, As, H	LSP	Agricultural land suitability	No
Wali, Datta, Shrestha, and Shrestha (2016)	Develop a land suitability model	P, IWU, T, LGP, RH, Wind, H, S, SG, Fertility, Dep, Silt, Clay, Sand, pH, OM, ESP, N-P-K, SE, Market, Road, Agri-input, income, labor force, market information, farmers' motivation, capital investment	AHP	saffron	No
Yan, Shi, Yan, and Chun (2017)	A spatial distribution model to study the spatial distribution of livestock manure and livestock manure nitrogen load on farmland at a patch scale	LULC, S, distance to farmland, water, habitation, forest land, road, market	AHP and WLC	Farmland	No

List of abbreviations: Temperature (T), dry month/ length of dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), available nutrient/Fertility (total N, P2O5, K2O), Slope (S), Aspect (As), Elevation (H), land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Depth to water-table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity(EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% CaSO4), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC).

Table A3
Fuzzy applications in ALSA.

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
Reshmidevi et al. (2009)	GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds	Dry days, water body, H, LULC, Tex, S, Dep, Drain, pH, CEC, OC, ESP, P, T, road	Fuzzy, WLC	Paddy fields	No
Feng et al. (2017a)	Quantitative impact of land qualities on rubber production	Dep, Ca, Mg, K, CEC, OC, pH, D, Water availability, H, Workability, S	Fuzzy, Maximum Limiting factor, Storie	Ruban	No
Burrough et al. (1992)	Classification to determine land suitability	H, sand, clay, ESP, Dep	Fuzzy	Agriculture	No
Zabel et al. (2014)	Global Agricultural Land Resources and land suitability evaluation	T, P, Tex, Coarse fragments, CaSO4, BSP, pH, OC, EC, ESP, S	Fuzzy	16 crops	No
(Ahamed et al. 2000)	To evaluate the arable land suitability for the given crops	Tex, Drain, Gravel, CEC, BSP, pH	Fuzzy	finger millet, paddy and groundnut	No
Avellan et al. (2012)	Differences in topsoil properties for the dominant soil mapping units between two global soil datasets.	S, Tex, Coarse fragments, CaSO4, BSP, pH, OC, EC, ESP, T, P	Fuzzy	Barley, Cassava, Groundnut, Maize, Millet, Oil-palm, Potatoes, Rapeseed, Rice, Rye, Sorghum, Soy, Sugarcane, Sunflower, Wheat	No
Baja, Chapman, and Dragovich (2002a)	Development of a conceptual model for defining and assessing LMUs from available biophysical information	CEC, OM, EC, Drain, Dep, Tex	Fuzzy	cropping land utilizationtype and soil loss index	No
Braimoh, Vlek, and Stein (2004)	Land suitability evaluation	OC, CEC, Drain, pH, Clay, Sand	Fuzzy	Maize	No
Bagherzadeh and Gholizadeh (2016)	To evaluate land suitability for irrigated sugar beet crop	LGP, T, H, SE, EC, ESP, OC	Fuzzy	sugar beet crop	No

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Table A3 (*continued*)

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
Dubovyk, Menz, and Khamzina (2016)	Provide spatially explicit guidance in support of afforestation land rehabilitation efforts	IWU, proximity to canal, canal density, collector density, GW, EC, S, proximity to collectors	Expert knowledge, Fuzzy, WLC	degraded irrigated cropland	No
Kurtener et al. (2008)	Application of fuzzy indicators for the evaluation of agricultural land suitability	Tex, pH, OM, N-P-K,	Fuzzy	Agricultural system	No
Joss et al. (2008)	Land suitability for afforestation	SG, SM, GDD, H, P, LULC	Fuzzy	Afforestation of hybrid poplar	No
Davidson et al. (1996)	Agricultural planning	LULC, Drain, Tex, Gravel, S, SE, CaCO3, SG, IWU, P, Sand, silt, clay, EC, pH, OM, CEC	Boolean logic, Fuzzy	tomatoes and cucumbers	
Zoccali et al. (2017)	land suitability analysis	T, Road, hydrological network, H, LULC	Fuzzy	Beekeeping	No
Feng et al. (2017b)	Suitability of marginal lands	Dep, pH, P, S, EC, GDD, LULC,	Fuzzy, OAT, WLC	Switchgrass, Miscanthus and hybrid poplar	No
Lewis et al. (2014)	Spatial suitability modeling approach	Modeled switchgrass yield , Market land value per acre, Expiring CRP acreage, Cropland Data	Fuzzy	Switchgrass	
Mbūgwa G. et al. (2015)	Understanding of the regional suitability of the crop	Diurnal T flux, P	Fuzzy	Burclover	No
Nguyen et al. (2015)	Design a GIS-based multi-criteria land suitability analysis	DM, T, S, Flood, Drain, Tex, Dep, CEC, N, OC, SE, road	Fuzzy, WLC	Rubber	No
Holzkämper et al. (2013)	Evaluation of crop-specific climate suitability	T, P, H, GDD, SR, AET, LPP	Rule-based approach, expert knowledge	Maize	No
Tuan, and Qiu, J. jun, Verdoodt, A., Li, H., and Van Ranst, E. (2011)	Review the suitability of temperature and precipitation for the winter wheat and summer maize cropping system	T, P, LGP	Fuzzy, WLC, Multiplicative	Winter Wheat and Summer Maize	No
Baja, Chapman, and Dragovich (2007)	To develop spatial modeling procedures for a MCE	road proximity, and water proximity, Hydrologic soil group, LULC	compromise programming (CoPr), fuzzy set approach and AHP	Land use planning	No
Tang and Van Ranst (1992)	Land indices and suitability classes for maize using the fuzzy set theory	P, T, SH, Drain, Tex, Dep, coarse fragment, CEC, BSP, OC	Fuzzy set	Maize	No
Baja, Chapman, and Dragovich (2002-b)	Develop analytical procedures of land-suitability evaluation in sloping areas	S, Drain, Gravel, Cobbles, EC, ESP, WHC, Tex; Dep, CEC, pH, OM	Fuzzy approach	Barley, cotton, spinach wheat, rye, corn pear, apple, orange sugar, beet sorghum, oats, clover citrus, peach, maize	No
Sicat et al. (2005)	Fuzzy modeling of farmers' knowledge for agricultural land suitability	Cropping season, SG, LULC, Tex, Dep, S	factor map based Fuzzy and farmers' knowledge	Agricultural systems	No

List of abbreviations: Temperature (T), dry month/ length of dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), available nutrient/Fertility (total N, P2O5, K2O), Slope (S), Aspect (As), Elevation (H), land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Depth to water-table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity(EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% CaSO4), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC).

Table A4
Examples of machine learning case studies for ALSA.

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
Wang (1994)	Agricultural land suitability assessment	T, P, DM, Drain, Tex, Dep, CEC, pH, N-P-K, ESP, S	ANN	Wetland rice, soybean, sugarcane, pasture and acacia	No
Mas et al. (2004)	Spatial distribution of tropical deforestation	Road, LULC, H, S, SG	ANN	Deforestation and agricultural system	No
Bagherzadeh and Gholizadeh (2016)	To evaluate land suitability for alfalfa	LGP, P, T, RH, Tex, EC, ESP, CaCO3, Gravel, Dep, OC, pH, S, Drain, Flood, CaSO4	ANN, TOPSIS	Alfalfa	No

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Table A4 (*continued*)

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
Bagherzadeh et al. (2016)	To evaluate land suitability for soybean production in a semi-arid region	P, T, RH, LGP, Tex, EC, ESP, CaCO3, Gravel, Dep, OC, pH, S, Drain, Flood, CaSO4	ANN, Fuzzy	Soybean	No
Jiao & Liu, 2007	Land suitability evaluation	OC, Tex, Water Conservancy, Thickness of tilth, S, N-P-K, pH	Fuzzy NN, GA	Paddy field evaluation	No
Ranjitkar et al. (2016)	Analyze and model current and projected future bioclimatic conditions to assess the suitability	AI, Diurnal T, P, PET, As, S, LULC	Global Environmental Stratification Strata (GenS), ecological niche modelling (ENM), Fuzzy	Banana and Coffee	Yes
Estes et al. (2013)	To compare suitability and productivity estimates for a well-understood crop species	LULC, SG, P, T, SR, H	MAXENT, GAM, DSSAT	Dryland maize	No
Ovalle-Rivera et al. (2015)	Global distribution of climates suited for growing Arabica coffee	T, P, Diurnal T	MaxEnt	Arabica coffee	Yes
Austin, Kasibhatla, Urban, Stolle, and Vincent (2015)	Quantify the potential CO2 emissions reductions achievable and the implementation of low emissions land use strategies	LULC, roads, rivers, H, S, P, T, Dep, pH, Drain, OC	Logistic Regression	Oil palm	Yes
Heumann et al. (2011)	Application of presence-only data for crop suitability modeling	LULC, GPS points, H, SG, SR, S, As, Wetness, pH, N, P, Tex	MaxEnt	Upland cassava and lowland paddy rice	No
Heumann et al. (2013)	Understand what factors of the natural, built, and social environment correspond to crop occurrence based on land use choices made by households	H, SG, roads, Population, LULC	MaxEnt	Cassava, rice	No
Kidd et al. (2015)	Regional Digital soil and enterprise suitability assessment	Dep, pH, EC, Clay, Drain, SS, Frost 0 days, T, P, Chill hours	Regression tree	Hazelnuts, potatoes	No
Liu et al. (2013)	Agricultural land evaluation	OC, Dep, pH, GW, irrigation garrantie rate, Tex, Drain	GA, Fuzzy	Agricultural land	No
Mosleh et al. (2017)	Suitable cultivable lands and water resources to optimize the cropping pattern	SG, LULC, coarse fragment, EC, pH, CaCO3, Tex, Dep, Existing pattern, Yield, Total cost, IWU, P, T	Goal Programming	Wheat, alfalfa, potato and maize	No
Passuello, Kumar, Cadiach, and Schuhmacher (2014)	Development of a land classification tool to determine whether Sewage sludge (SS) is suitable for organically amending a given agricultural soil	Distance to urban areas, pH, Tex, OM, S, P, T, river Metals concentration, CaCO3, GW, water bodies	Bayesian networks (BNs)	Sewage sludge amendment of agricultural soils	No
Holzkämper et al. (2013)	Rule-based approach for evaluating crop-specific climate suitability	T, P, H, Yield	Knowledge-based determination of factor suitabilities, rule-based approach, WLC, genetic algorithm (GA)	Maize	Yes
Läderach, Martinez-Valle, Schroth, and Castro (2013)	To present future climate scenarios for the main cocoa growing regions of Ghana and Côte d'Ivoire	P, T, AEP and other variables derived from P and T	MAXENT model	Cocoa	Yes
Kong, Lan, Yang, and Xu (2016)	Suitability assessment model	Geomorphic type, S, Soil nutrients, pH, soil pollution index, IWU, Drain, Roads, SE, GW	Back-propagation neural network (BPNN)	Agricultural land	No
Pilehforooshha, Karimi, and Taleai (2014)	A two stage model for crop allocation is presented	T, P, RH, S, Dep, Tex, Flood, Drain, income, H	Cellular automata (CA), Markov chain, fuzzy rule-based system, goal programming, WLC method	Wheat Barley Maize Alfalfa Potato	No
Wang et al. (2011)	Find out important factors influencing the quality of winter wheat and evaluate suitable land based on eco-environmental factors	T, P, SH, N, OC	ANN	Winter wheat	No
Yu, Chen, Wu, and Khan (2011)	To simulate an evaluation of irrigated cropland suitability	S, Tex, Dep, DWT, EC, HC, distance to stream and irrigation land use	Cellular automata (CA)	Irrigated cropland	No

List of abbreviations: Temperature (T), dry month/ length of dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), available nutrient/Fertility (total N, P2O5, K2O), Slope (S), Aspect (As), Elevation (H), land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Depth to water-table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity(EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% CaSO4), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC).

Table A5
Case studies of expert systems for ALSA.

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/ Agricultural systems	Climate change issue considered (Yes/No)
Ambarwulan et al. (2016)	Land resources and land suitability mapping	T, DM, P, Drain, Tex, Dep, CEC, BSP, pH, OC, N-P-K, S, SE, income	ALES	Rice	No
Kalogirou (2002)	Implementation of land suitability evaluation model	OC, BSP, CEC, CaCO3, CaSO4, pH, Dep, Gravel, SS, S, SE, SG, EC, ESP, Water level, Flood, Drain	Expert System Shell (LEIGIS)	Wheat, barley, maize, seed cotton, sugar beet	No
Kontoes, Wilkinson, Burrill, and S. G., and J. M. (1993)	Estimates of agricultural production from satellite imagery	LULC, Tex, Dep, Drain, WHC, Road	Knowledge-Based System	Agricultural land classification	No
Yizengaw and Verheye (1995)	An expert system in land evaluation	LGP, P, Frost hazard, T, Dep, Tex, Coarse fragments, flood, Drain, OM, CEC, EC, ESP, pH, S, SS	ALES	Barley, maize, and teff	No
de la Rosa et al. (2009)	Sustainable land use and management practices for selected Mediterranean benchmark sites	Dep, SS, Tex, WHC, reaction, OC, CEC, ESP, P,T	MicroLEIS DSS model	Agricultural system	No
D'haeze et al. (2005)	A goal of diagnosing the sustainability of the rapidly expanding Robusta coffee sector	BSP, CEC, OC, pH, S, Dep, Tex, SS, Drain, SG	ALES	Robusta coffee	No
Rabati, Jafarzadeh, Shahbazi, Rezapour, and Momtaz (2012)	Evaluate qualitative and quantitative land suitability for sunflower and maize crops	Dep, sand, silt, clay, Tex, CaCO3 CEC, EC, OC, pH, SG, P, T, PET, AI, LGP, unit price	MicroLEIS	Maize and sunflower	No
Wandahwa and Van Ranst (2014)	Land suitability analysis	Flood, Drain, Tex, Coarse fragments, Dep, CaCO3, CEC, BSP, pH, OC, EC, ESP, T, SM, DM, P, Night T	ALES	Pyrethrum achene	No
Manna et al. (2009)	Forage maize land suitability study by comparing different methods having increasing complexity and costs	SG, pH, EC, OC, BD, WHC, HC, GW, P, T, Drain, EVI, NDVI	MicroLEIS, WAP (Soil Water Atmosphere Plant) model, CropSyst	Forage maize	No
van Lanen et al. (1992)	Qualitative and quantitative physical land evaluation methods to evaluate crop growth potential in the European Communities (EC)	P, T, SR, wind, vapor pressure, and number of rainy days, Tex, S, Drain, Dep	ALES, WOFOST	Wheat-growing	No

List of abbreviations: Temperature (T), dry month/ length of dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), available nutrient/Fertility (total N, P2O5, K2O), Slope (S), Aspect (As), Elevation (H), land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Depth to water-table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity(EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% CaSO4), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC).

Table A6
The use of crop models and Agro-climatic indicators for ALSA

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
Liu et al. (2008)	Spatially explicit assessment of current and future hotspots of food insecurity in Sub-Saharan Africa (SSA).	Undernutrition data, Dep, sand, silt, BD, pH, OC, P, T, SR, WM, population, GDP	GEPIC	Cassava, maize, wheat, sorghum, rice, and millet	Yes
Liambila and Kibret (2016)	Evaluate the impacts of climate change on land suitability for rain-fed crop diversification	Dep, Tex, Drain, EC, ESP, PET, T, P, CEC, pH, OC	Almagra Model, Sys	Sweet potato, sorghum, maize, soybean, wheat	Yes
Lane and Jarvis (2007)	Identify the crops and regions potentially most afflicted by climate change	Monthly P and T	ECOCROP model	groundnut, soya, sugar cane + more other crops	Yes
Ramirez-villegas et al. (2013)	Assessing impacts of climate change on agriculture	P, T	ECOCROP model	sorghum	Yes
Kenny et al. (1993)	Agro-climatic suitability and effects of climate change	P, T, AWC	Water Deficit Method	grain maize, winter wheat and cauliflower	Yes
Daccache et al. (2011)	map current and future land suitability	Dep, LGP, Tex, OM, S, SS, P, T, AET	Pedo-climatic functions, PSMD	Potato	Yes
De Silva et al. (2007)	To assess the spatial variation of the impacts of climate change on paddy irrigation	T, SR, Wind, RH, P, AEP, IWU	Spreadsheet model based on CROPWAT methodology	Rice	Yes
Brown, Towers, Rivington, and Black (2008)	Mapping of soil properties using the wetness vulnerability index	WHC, P, PET, SM, Wetness, SG, Dep, Tex	Wetness Vulnerability index	Agricultural system	Yes

(continued on next page)

Table A6 (*continued*)

Reference	Main purpose of the study	Major Criteria considered	Model/Method	Crop/Agricultural systems	Climate change issue considered (Yes/No)
Caubel et al. (2015)	Develop an assessment method for crop-climate suitability	P, T, Frost, Heat, SR, sowing day frequency, Wind, AET, WHC	Agro-climatic indicators	maize, wheat, grape	Yes
Ramankutty, Foley, Norman, and McSweeney (2002)	Quantitative global estimates of land suitability for cultivation based on climate and soil constraints	GDD, AET, PET, pH, OC, P, SM	Surface Energy, Water balance model	Croplands	Yes
Holzkämper et al. (2011)	Spatiotemporal evaluation and analysis of climate suitability for different crops	SR, P, T, AET, LGP	Agro-climatic indicators	Maize	Yes
Confalonieri et al. (2013)	Develop crop suitability software	T, heat stress, Drain, Coarse fragment, OC, sand, clay, Dep, S, EC, ESP, CaSO4, SM, P, PET	FAO Ecocrop, the Less Favoured Areas (LFA) approach, the Direct Crop Suitability Discriminant (DCSD)	Wheat	Yes

List of abbreviations: Temperature (T), dry month/ length of dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), available nutrient/Fertility (total N, P2O5, K2O), Slope (S), Aspect (As), Elevation (H), land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Depth to water-table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity(EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% CaSO4), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2019.02.013.

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